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Automating landslips segmentation for damage assessment: a comparison between deep learning and classical models

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Abstract. Natural disasters have a significant effect in terms of impacted individuals and casualties. Artificial Intelligence (AI) techniques for automatically segmenting landslides from aerial photos is a relatively new field of research. Segmenting landslips quickly and accurately can significantly aid in assessing the damage caused by natural disasters. This research aims to compare the performance of AI techniques with more classical methods for the automatic segmentation of landslides from aerial images for damage assessment.
It is presented a dataset of satellite images containing landslides collected in the Broni (Italy) region and annotated to train and test the segmentation model. Both classical image processing techniques, such as thresholding and edge detection, and AI-based methods, such as U-Net, are applied to the dataset.
Overall, this research demonstrates that AI-based methods are a promising tool for automatically segmenting landslides from aerial images and can be a powerful asset in assessing the damage caused by natural disasters. The study also highlights the importance of combining classical and AI-based methods for better performance, especially in challenging and complex scenes.

Keywords: Semantic Segmentation, Artificial Intelligence, Landslips, Damage Assessment.

1 Introduction

Landslides are a significant geological hazard that causes death, property damage, and interruption of transportation networks. Catastrophic events have more than doubled globally in recent years [1]. Monitoring and predicting landslides is a critical task that can help mitigate their impact. In recent years, satellite imagery has become a valuable tool in landslide detection and monitoring [2]. Satellite images offer a wide coverage area and allow frequent monitoring of areas prone to landslides. Damage assessment using satellite images can be critical in determining the impact of devastating events [3].

On the other hand, analysing satellite photos for landslide identification and hazard assessment is a complex process. Landslide features can be tiny and difficult to see, and air conditions and other noise sources might influence images. The manual process of segmentation (the sketching of a closed path of lines to encircle a significative area in an image) is painstaking and time-consuming. As a result, automated systems for analysing satellite photos for landslide identification and monitoring could help reduce operators' workload.

Deep learning and traditional computer vision segmentation approaches have emerged as valuable tools for image analysis tasks. Deep learning approaches, such as convolutional neural networks (CNNs), have demonstrated extraordinary success in picture segmentation tasks, achieving state-of-the-art performance in various applications. Besides, traditional computer vision approaches such as edge detection and thresholding have been widely employed for picture segmentation applications and are computationally efficient.

This paper investigates segmentation techniques using deep learning (U-Net [4]) and classical computer vision methods for landslide detection in satellite images for damage assessment. We aim to compare the performance of those techniques and evaluate their suitability for different types of landslides and image conditions. Specifically, we will focus on the following objectives:

- Investigating the performance of classical computer vision methods for landslide segmentation;
- Testing a deep learning U-Net segmentation model for landslide detection in satellite images;
- Comparing the performance of deep learning-based and classical computer vision-based segmentation methods for landslide detection in satellite images;

The results included in this study can help improve the efficacy of segmentation algorithms for landslide detection in satellite or aerial pictures, as well as inform the development of automated landslide analysis systems.

The problem of hydrogeological instability is increasing in importance in Italy. Developing segmentation techniques can help monitor existing landslides (improving social sustainability) and damage assessment. Very often, after intense phenomena, public bodies have to assess the damage quickly to pay compensation requested by the affected parties. A system of this type could help public administrations quickly map the areas affected by natural disasters, avoiding fraud and supporting those damaged (addressing economic sustainability) and suggesting places to be avoided to build on (environmental sustainability).

2 Classical Computer Vision methods

Nowadays, landslides can be identified and monitored using images taken from satellites, manned aircraft or helicopters or autonomous aerial vehicles. Landslide zones may be segmented from pictures using a variety of approaches, including thresholding, edge detection, and the Canny algorithm. This chapter will examine how these classical strategies for image analysis can be used to segment landslides from aerial/space images.

2.1 Thresholding

Thresholding is a typical image processing technique that segments images based on pixel intensity values. It involves setting a threshold value and then classifying pixels above or below this value as belonging to different objects in the picture. In landslide segmentation, thresholding can separate landslide areas from the surrounding terrain based on pixel intensity values.

We first need to select an appropriate threshold value to implement thresholding for landslide segmentation. This can be done using various methods, such as Otsu's or maximum entropy [5]. Once the threshold value is determined, we can apply it to the images using a simple thresholding function. This will classify each image pixel as belonging to the landslide area or the surrounding terrain.

2.2 Edge detection

Edge detection is a technique to identify the boundaries between objects in an image. In the context of the segmentation, edge detection can determine the edges of the landslide area, which can then be used to accurately segment the site from the surrounding terrain.

There are various edge detection algorithms available, such as the Sobel [6], Prewitt [7], and Roberts operators [8]. These operators work by calculating the gradient of the image intensity values and identifying areas of rapid change in intensity, which correspond to the edges of objects in the image.

To implement edge detection for landslide segmentation, we can first apply a smoothing filter to the satellite image to reduce noise and enhance edges. We can then use an edge detection algorithm to identify the edges of the landslide area. The resulting edge map can then be combined with the thresholded image to segment the landslide area more.

2.3 Canny Algorithm

The Canny edge detection algorithm was proposed by John Canny in 1986 [9] and has become a standard method for edge detection in computer vision and image processing. The algorithm aims to detect the edges of an image by finding the points of maximum gradient magnitude in the picture. The algorithm has several steps: smoothing, gradient calculation, non-maximum suppression, and thresholding.

In the context of the present research, the Canny edge detection algorithm can extract the boundaries between the landslide areas and the surrounding terrain. Landslides are characterised by abrupt changes in elevation and slope, which the edge detection algorithm can detect.

Several studies have successfully applied the Canny edge detection algorithm for landslide segmentation from satellite images. For example, [10] used the Canny edge detection algorithm to extract the boundaries of landslide areas from optical images in Greece. They compared the results with other edge detection algorithms and found that the Canny algorithm performed better in accuracy and efficiency. Similarly, [11] used the Canny edge detection algorithm to extract the boundaries of landslide areas from SAR images in China.

3 U-Net for landslips segmentation

Segmentation of landslides from remote sensing images is crucial for disaster management and damage assessment. Manual segmentation of landslide areas is time-consuming, wearing for operators, and prone to human error. Thus, there is a need for an accurate and automated method for landslide segmentation. In recent years, deep learning-based approaches have shown promising results in various image segmentation tasks [12–15]. U-Net's design enables rapid and precise segmentation of landslide features from satellite or aerial imagery [16–18]. The network learns to recognise landslide phenomena such as soil erosion, rock falls, and debris flows using a modest number of training instances. U-Net's architecture makes it simple to apply and adapt to diverse datasets, making it an appropriate tool for landslide segmentation in various locales and environmental situations. Adopting U-Net as a novel and accessible technology for landslide segmentation has enormous promise in disaster management and preventive efforts. Thanks to the model's ability and knowing the camera's resolution, it could be possible to compute the area interested in the landslip rapidly and precisely to accelerate the damage assessment process.

3.1 U-Net Model

The U-Net architecture was proposed by Ronneberger in 2015 [4] for biomedical image segmentation. It is a convolutional neural network consisting of two parts: the contracting and expansive paths.
The contracting path consists of repeated application of 3x3 convolutional layers, followed by a Rectified Linear Unit (ReLU) activation function and a 2x2 max-pooling operation with stride 2. This operation reduces the spatial resolution of the feature maps while increasing their depth. The final feature map from the contracting path is then passed to the expansive path.
The expansive path consists of repeated application of 2x2 up-convolutional layers, increasing the feature maps' spatial resolution while reducing their depth. A concatenation follows each up-convolutional layer with the corresponding feature map from the contracting path and a 3x3 convolutional layer with ReLU activation. The concatenation operation enables precise localisation by providing high-resolution features from the contracting path to the expansive path.
The final layer of the U-Net model is a 1x1 convolutional layer with a sigmoid activation function, which produces the probability map of the segmentation mask. Fig. 1 it is shown the general architecture of the U-Net model.

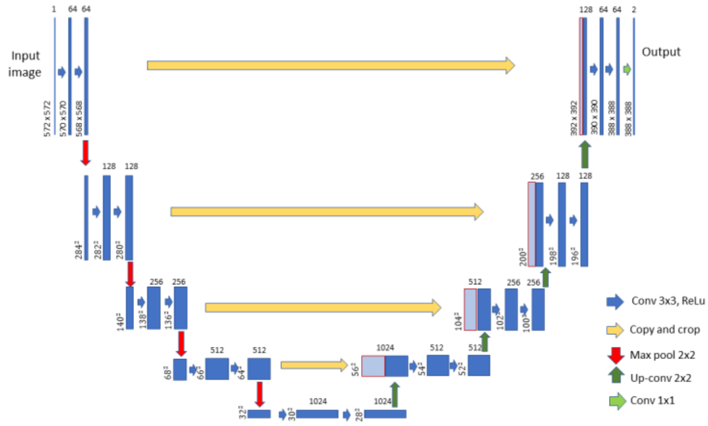

Fig. 1. General U-Net architecture.

4 Implementation

The dataset used in this study consists of 32 high-resolution aerial images of the region of Broni (Italy) taken from a fixed-wing manned aircraft. Every landslip contained in the photos was manually segmented. The Landslide Inventory Map of the study area was used as ground truth data to evaluate the accuracy of the segmentation methods. Fig. 2 it is represented an example of the dataset used.

Fig. 2. Example of a dataset representing landslides manually segmented in the region of Broni (Italy).

Traditional computer vision approaches were used to segment the landslides in the dataset. The photos were binarised using thresholding algorithms to create a binary mask of the landslides. The Otsu approach was used to determine the best threshold value for distinguishing the pixels of the landslides from the background. The Sobel operator and the Canny edge detection method determined the landslide borders. Unfortunately, the findings from these approaches were unsatisfactory because they failed to represent the landslides' intricate properties, such as their irregular forms and textures. Fig. 3 below illustrates an application of thresholding, Otsu, Sobel and Canny edge detection to a landslide aerial photo.

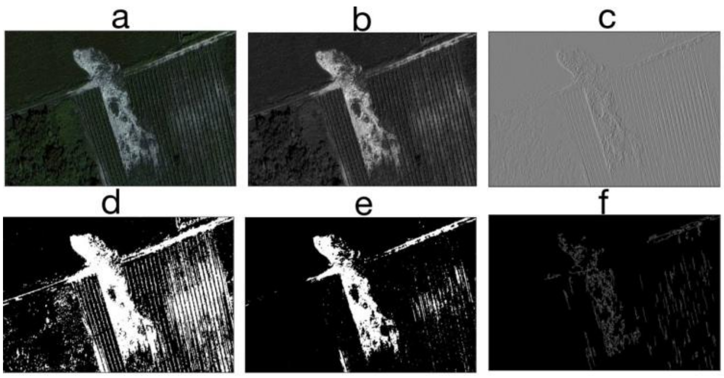

Fig. 3. Application of classical Computer Vision methods to dataset representing landslides of the Broni region (Italy): a) original image, b) original grey image, c) application of Sobel edge detection, d) application of global thresholding, c) application of Otsu thresholding, d) application of Canny edge detection.

To apply U-net to the landslips dataset, the first step is to prepare the dataset. The images should be of high resolution to ensure accurate segmentation. The dataset was then split into training and validation sets. The loss function used to measure the difference between the predicted and ground truth segmentation maps was the Binary Cross Entropy shown in eq.1.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(p(y_i)) + (1 - y_i)\log(1 - p(y_i)) \tag{1}$$

Where y is the label (1 for landslide and 0 for background), and $p(y)$ is the predicted probability of the pixel being a landslide for all N pixels.

During the training, the U-Net model needs the original RGB image containing the landslide and the associated mask in which the corresponding landslip was manually segmented; the mask represents pixels completely white if corresponding to a landslide otherwise are black.

Our U-Net model was trained for 50 epochs using a batch size of 4, with input image sizes of 700x620 and a learning rate of $l_r = 0.001$.

The model achieved an accuracy of 82.59, with a loss of 0.166 and a dice score of 0.438. Fig. 4 shows an example of segmentation produced by the model.

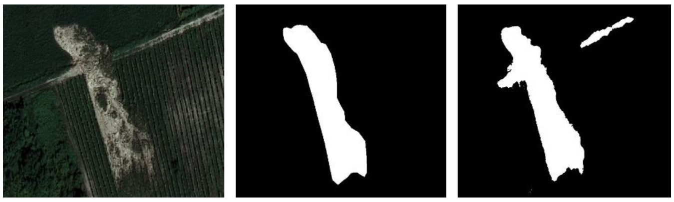

Fig. 4. U-Net implementation. The left image represents the original RGB, the centre corresponds to the manually segmented mask, and finally, the right image shows the output produced by U-Net.

It should be noted that the model has been trained using only 28 images. Typically, deep learning models need thousands of photos to be correctly trained. The results shown in Fig. 4 are much better than the mask output using classical methods. However, it is essential to report the difficulty of the model to segment landslips covered by vegetation and not clearly distinguishable, as reported in Fig. 5.

Fig. 5. Difficulties of U-Net model segmentation.

5 Conclusion

The segmentation of landslides in satellite images is a challenging task due to the complexity of the natural environment and the variability of landslide features. Classical computer vision methods, such as thresholding and edge detection, have been widely used for image segmentation. However, these methods may not be efficient in identifying the complex features of landslides. U-Net, a convolutional neural network architecture, has shown promise in image segmentation, including landslide segmentation. This paper presents a preliminary assessment of the performances of different image analysis techniques, and a wide range of improvements is required to obtain better results. In order to deeply understand the capacity of such models, the dataset needs to be enlarged, possibly including new data such as near-infrared images. It is also essential to analyse the possible modifications implemented in U-Net to enhance its segmentation ability. Last but not least, a study about the dual implementation of classical computer vision methods with U-Net could be beneficial: a possible strategy to improve the results could be to apply a thresholding method to the images and then merge the original RGB images with the corresponding results of the thresholding and then using the resulting pictures to train the U-Net model.

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