Ridge-i Large-Scale Landslides Detection from Satellite Images with Incomplete Labels

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INTRODUCTION

Earthquakes and tropical cyclones cause the suffering of millions of people around the world every year. The resulting landslides exacerbate the effects of these disasters. Landslide detection is, therefore, a critical task for the protection of human life and livelihood in mountainous areas. To tackle this problem, we propose a combination of satellite technology and Deep Neural Networks (DNNs). We evaluate the performance of multiple DNN-based methods for landslide detection on actual satellite images of landslide damage using the capabilities of a high-performance GPUs. Our analysis demonstrates the potential for a meaningful social impact in terms of disasters and rescue.

Experimental Results

Patch-based classification

• ResNet50 [1]

Semantic Segmentation

• DeepLabv3+[2]

Dataset

- Dataset A: 20000 × 18957 x 3
- Dataset B: 43008 × 36864 x 3



dataset A



dataset B

Overview of Methods

We applied landslide detection methods based on multiple DNNs and compared them. In this section, we introduce several DNN-based methods for landslide detection in satellite images.

Patch-Based Binary Classification

In Patch-Based Binary Classification, we divide the input image into patches of a certain size and classify the presence of landslides for each patch.

We use this approach as a baseline, as it is a very orthodox convolutional neural network based approach. We adopted the ResNet50 [1] as the architecture.

• Train : Test = 0.5 : 0.5



Qualitative evaluation for both dataset A and dataset B. The landslide area in dataset A is visualized using several methods. On the other hand, because dataset B lacks label information, we visualized it using only the anomaly detection method.

Table 1. Qualitative evaluation of patch-based binary classifier for dataset A. This

Semantic Segmentation

We applied DeepLabv3+ [2], a pixel-by-pixel classification method. This is one of the most successful semantic segmentation models.

With the disadvantage of higher annotation costs compared to the baseline, it allows more precise predictions. We need to select the method appropriately considering the trade-off between annotation cost and detection accuracy.

Unsupervised Anomaly Detection

Supervised landslide detection is powerful, but has several drawbacks: (1) Annotation is required. Such annotations require costly domain expertise. (2) Label imbalance. In general, since disasters are rare, so are contemporary labels.

To tackle this problem, we propose an unsupervised anomaly detection method. There are several such methods using DNNs.



shows that performance is sufficient to understand where landslides are occurring.

Network (dataset)	Accuracy (%)	F1 Score	Precision	Recall
ResNet50 (train)	93.5	0.663	0.572	0.788
ResNet50 (test)	89.0	0.660	0.542	0.846

Table 2. Qualitative evaluation of semantic DeepLabv3+ and Anomaly U-Net for dataset A. DeepLabv3+ can detect landslide areas with high accuracy, but require meticulous annotation. Despite these accuracy limitations however, the Anomaly U-Net permits a rough damage assessment without label information.

Method	Mean IOU	Annotation
DeepLabv3+	0.8105	Supervised
Anomaly U-Net	0.7102	Unsupervised

REFERENCES

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Proposed unsupervised landslide detection method (Right):

- Input: Normal Images (not contain landslides) + **Noise**
- Output: Noise removed Images

 $\mathcal{L} = \mathcal{L}_r(x, f_r(x+z)), \quad z \sim \mathcal{N}(0, 1)$

We use U-Net [3] as the noise removal component f_r

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