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# FUSION NETWORK AND OPEN ACCESS DATASET FOR LANDSLIDE DETECTION: A COMPARATIVE ANALYSIS ON BIJIE AND HOKKAIDO DATASETS

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## ABSTRACT

Remote sensing techniques are increasingly employed for early detection of ground deformation and landslide warning systems. The combination of vast remote sensing data and advancements in machine learning algorithms has led to significant progress in landslide detection and mapping.

This study proposes an innovative neural network architecture for landslide detection. The network utilizes a fusion of optical images (RGB) and Digital Elevation Models (DEMs) to enhance accuracy. Additionally, attention layers and Mixup techniques are incorporated to further improve the model's performance. Given the limited availability of training data, the proposed network was trained on a publicly accessible dataset, specifically the established Bijie landslide dataset located in China. We demonstrate that using an efficient training strategy on this dataset allows us to pretrain a network that can be easily fine-tuned for a different site exhibiting landslides at various scales. In practice, we introduce a newly developed dataset covering the southwestern part of Hokkaido, Japan, which experienced a landslide event in 2018. This dataset is freely available on the internet. The results demonstrate the effectiveness of the proposed architecture compared to existing methods, highlighting the benefits of our pretrained model.

**Index Terms**— Landslide detection, fusion network, attention, open datasets

## 1. INTRODUCTION

Remote sensing techniques have gained widespread adoption for early detection of ground deformation, establishment of warning systems in the event of impending landslide initiation, and mid- to long-term monitoring of slope instability. The vast amount of data accessible to the scientific community, coupled with improved processing techniques as data volumes have increased, has led to remarkable advancements in the field of remote sensing data processing, particularly through the utilization of machine learning algorithms and deep neural networks.

This arsenal of data and techniques is crucial for meeting the current scientific challenges that the landslide research community still faces. Landslides can be intricate, necessitating precise knowledge of their location, shape, and size for effective risk management and disaster mitigation strategies. One crucial goal is to automate landslide detection and mapping, particularly through learning methods. Machine learning methods based on Deep Neural Networks have recently been employed in landslide studies, producing promising and efficient results for landslide detection [1, 2, 3].

In this study, we propose an original neural network for landslide detection. This network is trained on the Bijie landslide dataset (more than 2 500 patches) already available [4]. We demonstrate that this trained network can be easily adapted to detect landslides with varying characteristics at other landslide areas, even with minimal data available.

In practice, we utilize a fusion network [5] dealing with optical images on the one hand and Digital Elevation Models on the other hand. To improve the results, attention layers [6] (able to stabilize the training and more precise results), as well as Mixup techniques [7, 8] (able to generalize more efficiently), are employed. We demonstrate that using a pre-trained network on existing datasets (e.g., the Bijie dataset) allows for easy fine-tuning on a new dataset with limited data available (Hokkaido dataset), although the embedded landslides appear at different scales. In addition to this methodological aspect, we also provide, in open access, the Hokkaido dataset.

## 2. STUDY AREAS

For this application, two different study areas affected by numerous landslides have been selected. Both containing images and Digital Elevation Models.

- **Bijie Dataset:** this large dataset (2 700 images mixing landslide/non-landslide images) is high-quality open-source dataset of satellite images of landslides in Bijie, China. The dataset has been used to evaluate the

effectiveness of new landslide detection methods and is available here : [http://gpcv.whu.edu.cn/data/Bijie\\_pages.html](http://gpcv.whu.edu.cn/data/Bijie_pages.html);

- **Hokkaido Dataset:** we have compiled a Hokkaido landslide dataset from high spatial resolution RGB images (Sentinel-2) and 10m elevation models<sup>1</sup>, triggered by a  $M_w$ 6.6 earthquake in 2018 [9]. The small dataset (70 images) encompasses more than 7 800 landslides within the Hokkaido region (Japan) mixing shallow and deep landslides with various sizes. We provide the dataset used for training our network here : [http://www.github.com/karstCand/HokkaidoLandslide\\_dataset/](http://www.github.com/karstCand/HokkaidoLandslide_dataset/).

### 3. METHODOLOGY

To detect landslides, we propose an original deep neural network that combines both digital elevation models (DEMs) and RGB images. Our network consists of three main stages:

- **Encoding:** We use separate encoders to extract features from the DEM and the RGB images independently. The DEM and RGB encoders are residuals convolutional neural network (residual-CNN);
- **Fusion:** features of RGB and DEM are fused in the latent space and used for the decoding part;
- **Decoding:** The decoder is also composed of residuals convolutional networks where attention layers are used to improve the performance of our model. Attention layers allow the model to focus on specific features in the input data. Skip connections, based on the sum of corresponding RGB and DEM encodings, are performed.

The overall network can be seen in figure 1.

To prevent both from the fact that few samples may be available and from overfitting, the network is trained using Mixup data augmentation. The initial idea behind Mixup is to randomly combine two learning samples  $X_1$  and  $X_2$  to create a new one  $X_n$  such as  $X_n = \alpha X_1 + (1 - \alpha)X_2$  and  $\alpha$  randomly chosen in the range  $[0, 1]$ . Associated output is then balanced accordingly and is no longer a binary probability with value 0 or 1 but is now a more fuzzy number in the whole range  $[0, 1]$ . This method is valuable for enhancing training data diversity, generating more challenging examples for machine learning models. By mitigating overfitting, Mixup helps models generalize better to unseen data. Additionally, it can contribute to training efficiency by allowing models to learn from a smaller dataset. Mixup has been successfully applied in computer vision for image classification, object detection,

<sup>1</sup><https://fgd.gsi.go.jp/download/menu.php>

and image segmentation, as well as in natural language processing for tasks such as machine translation, text summarization, and text generation.

## 4. EXPERIMENTAL RESULTS

### 4.1. Bijie Dataset

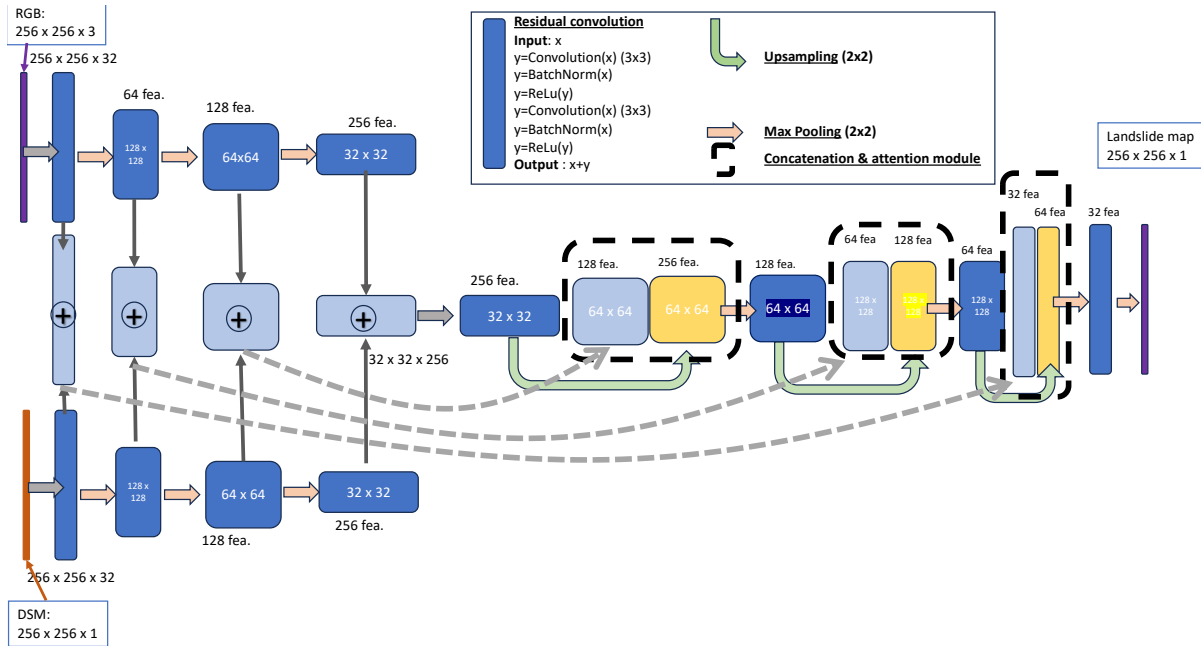
We trained, tested, and validated our neural network on Bijie dataset, and compared the results for various architectures and with existing ones. Our approach systematically outperforms the others. Some illustrations of landslide detection for the Bijie, as well as estimated attention maps, are visible in Figure 2. On this figure, an input image, the ground truth, the estimated landslides, an attention map superimposed to the original image and an example of feature are depicted. The first example (first line) shows a detection in an easy situation (the visualization of the landslide appears clearly) whereas the second example (second line) is more challenging, since the landslide is older and the vegetation has grown in the meantime where the landslide appeared. As can be seen, both landslide detection and attention maps are consistent. Quantitative results for  $F_1$  score on Bijie dataset are also visible in Table 1, with and without Mixup and for three different RGB backbone encoders (VGG, residual-unet and simple unet, these two latters being trained from scratch). The quantitative values affirm the consistently strong performance of our approach and indicate that retraining the encoder is more beneficial in this scenario. Remote sensing data, indeed, displays distinct properties compared to the typical RGB images used for training VGG. The benefit of Mixup training appear also clearly in these experiments.

**Table 1. Quantitative evaluation** ( $F_1$  score) on the Bijie dataset for three different backbones

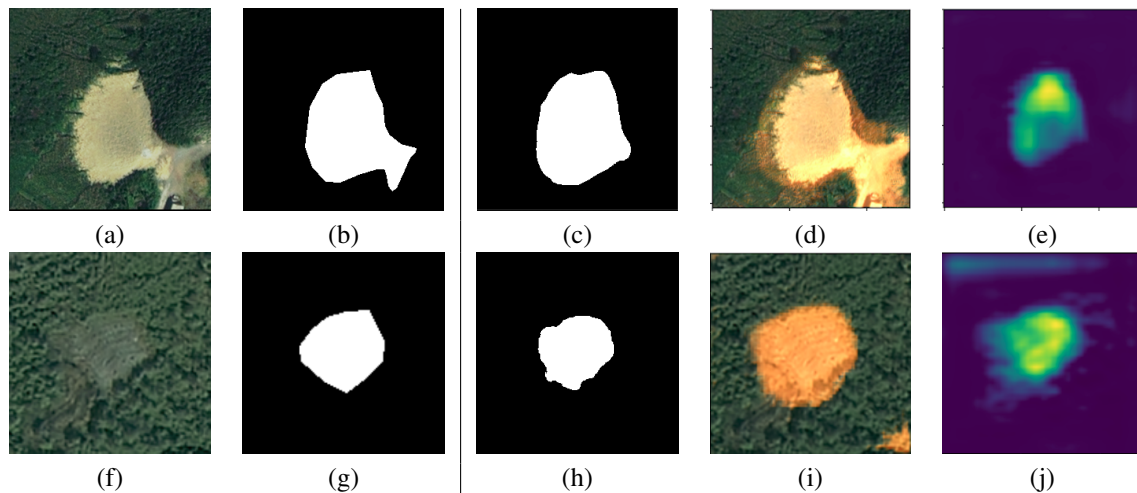
Backbone	No Mixup $F_1$ score	Mixup $F_1$ score
VGG	0.738	0.823
Residual Unet	<b>0.755</b>	<b>0.850</b>
Unet	0.724	0.840

### 4.2. Hokkaido Dataset

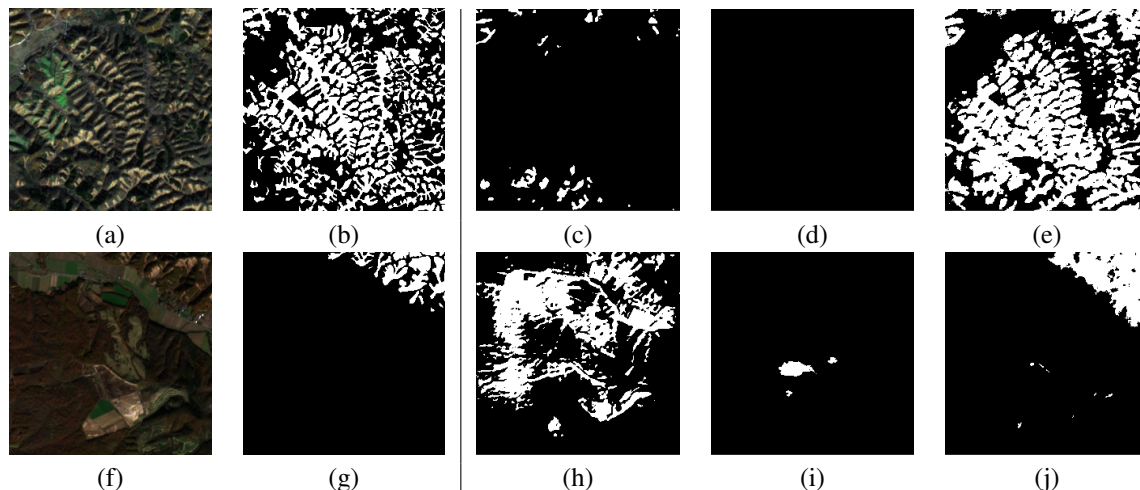
In this part, we aim to apply our model to a small dataset (Hokkaido) consisting of only 40 training images, 15 validation images, and 20 test images. Initially, we attempt to train the model from scratch. We then perform fine-tuning using the pretrained model on the Bijie dataset. The results are shown in Figure 3 (from scratch; using a pre-trained model without fine-tuning; using a pretrained model with fine-tuning). Quantitative results are provided in Table 2. These results obviously demonstrate the generalizability of the pre-trained model, which is capable of adapting to landslides



**Fig. 1. Landslide detection network** designed to detect landslides, based on the fusion of RGB and DEM data



**Fig. 2. Illustration of landslide detection on Bijie Dataset.** (a,f): two different RGB images; (b,g): associated ground truths; (c,h): estimated landslide areas; (d,i): attention maps superimposed to the corresponding RGB image; (e,j): random illustration of one feature. The landslide appears clearly in the first example but its visualization is more tricky in the second example. In both cases, estimated landslides, attention maps and features are consistent.



**Fig. 3. Illustration of landslide detection on Hokkaido Dataset.** (a,f): two different RGB images; (b,g): associated ground truths; (c,h): estimated landslide areas with a network estimated from scratch (on 40 patches); (d,i): estimated landslide areas with a network pre-trained on Bijie dataset without fine tuning; (r,j): estimated landslide areas with a network pre-trained on Bijie dataset with fine tuning on 40 patches. The benefits of pre-trained model obviously appear here since the network is able to estimate landslides of small size.

of different scales (Hokkaido exhibit very small landslides compared to Bijie) with only few fine tuning samples.

**Table 2. Quantitative evaluation ( $F_1$  score) on the Hokkaido dataset for different learning strategies**

From scratch	Without fine tun.	With fine tun.
$F_1$ score	$F_1$ score	$F_1$ score
0.79	0.832	<b>0.840</b>

## 5. CONCLUSION

In this paper, we have proposed a neural network for landslide detection that combines the strengths of digital elevation models (DEMs) and RGB images. Our approach uses attention layers to learn the importance of different features in the input data, and Mixup to improve the model’s generalization. We evaluated our approach on two datasets, including a new dataset that we collected ourselves. Our results show that our approach outperforms existing methods on the Bijie dataset, especially in challenging cases where landslides are obscured by vegetation or other features. This robustness to noise makes it suitable for detecting landslides in challenging conditions. As shown on Hokkaido, the pretrained model is easily generalizable to a new dataset with few samples, even if the shape and scale of the landslides are different. In future work, we plan to investigate the use of our approach for real-time landslide monitoring. We also plan to explore the use of other techniques, such as transfer learning, to further improve performance.

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