Disaster Area Detection by Deep Learning using UAV and Satellite Imagery

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ABSTRACT: Due to recent changes in the global environment, damage from disasters such as extreme weather, typhoons, and heavy rainfall has been occurring frequently. In this study, we investigated a method for disaster area detection using aerial images taken by UAV and satellite imagery in order to obtain detailed information on the damage at an early stage. A deep learning-based method was applied to detect damaged areas from aerial images and satellite imagery of disaster-stricken areas affected by Typhoon 19 and other disasters. The construction of a system that automatically detects damaged areas is expected to lead to an early understanding situation and a reduction in restoration costs.

1. INTRODUCTION

Natural disasters such as typhoons, earthquakes, and heavy rains cause, landslides, flooding, and damage to buildings over a wide area. If houses are damaged, the extent of the damage must be certified by a disaster notification certificate and the prescribed procedures must be followed (Cabinet Office, 2022). In the case of roads, rivers, and other public facilities, the controlling authority will calculate the amount of damage and disaster recovery costs. In any case, the wider the area affected and the more serious the damage, the longer it takes to calculate the amount of damage and restoration costs, and the more time will be required for restoration activities to be delayed.

Therefore, it is important to quickly assess the damage situation in a wide area using satellites and UAVs. Conventionally, the main method of identifying damaged areas has been human decipherment using images taken on site by manned airplanes. However, after a typhoon or heavy rain, it may be difficult to obtain sufficient information because of the low cloud cover and other difficulties in photographing. Therefore, local situation assessment using UAVs and wide-area situation assessment using satellite imagery are being conducted.

Several methods have been proposed for detecting disaster areas using aerial images and satellite imagery. For example, a method that determines whether an area is affected or not for each pixel of images (Ueda, 2018), or a method that determines an area by dividing an image into a certain size, have been proposed (Kimura,2019). In this study, we examined the application of object detection algorithms to the detection of collapsed houses, landslides, and flooded areas.

2. TARGET AREA AND DATA CONSTRUCTION

Aerial images taken by a drone at the site of the typhoon disaster were used as UAV aerial images. For landslides detection, aerial images of the Azumagawa area of the 2018 Hokkaido Eastern Iburi earthquake (Hokkaido earthquake) were obtained from Geographical Survey Institute maps (GSI Maps), and an attempt was made to detect landslides. Furthermore, for landslide detection from satellite imagery, Landsat-8 satellite imagery was used for model building and detection experiments.

2.1 Aerial images by UAV

512 drone images taken around the Yuzirigawa and Kaburagawa Rivers in Gunma Prefecture, damaged by Typhoon No.19 in October 2019 (Nakanojo Civil Engineering Office 2019, Tomioka Civil Engineering Office 2019), were

used to create train data. In addition, ortho-mosaic images were created by merging the drone images of each location. The damage areas were classified into 9 categories (9 classes) based on the assumption of damage to public facilities as well as houses. Although there are several definitions (Kamioka, 2018, Miura, 2020) for determining whether a house has collapsed or not, in this study, we used the following classifications: no damage, half collapsed (with/without blue tarps), and completely collapsed. The classification labels and the number of decoded data are shown in Table 1.

Table 1. Classification Categories and the number of training samples.

Label	Class Name	#Data
0.clp_offroad	collapsed offroad	0
1.clp_asphalt	collapsed asphalt	86
2.clp_river	collapsed river	368
3.landslide	landslide	275
4.non_clp_house	house	1696
5.bluetarp_house	blue tarp house	305
6.clp_house	collapsed house	6
7.half_clp_house	half collapsed house	427
8.bluetarp	blue tarp	1496

2.2 Satellite imagery

We attempted to detect landslides in satellite imagery taken by Landsat-8 of the Azumagawa area, where large-scale landslides occurred during the September 2018 Hokkaido earthquake. The acquired satellite imagery was taken on September 6, 2018, immediately after the earthquake, and on September 2, 2019, when the season was close to the time of the earthquake occurrence and cloud cover was low.

3. DISASTER AREA DETECTION METHOD

Various methods have been proposed for object detection from images. For example, a method has been proposed to classify each pixel in an image into a class to determine whether it is a damaged area or not (Ueda, 2018). Another method is to divide the image into a certain size in a grid pattern and determine the damage in each area (BintiAmit, 2017, Kimura, 2018). Many Transformers-based methods have also been proposed for use in the analysis of satellite imagery (Aleissaee, 2022).

In this study, we examined a method for detecting disaster areas by applying an object detection algorithm. Many methods based on deep learning have been proposed for object detection algorithms. For example, R-CNN (Girshick, 2014), SSD (Liu, 2016), YOLO (Redmon, 2016), and DETR (Carion, 2020). In this study, considering real-time detection from drone videos, we applied YOLO, which has a high detection speed.

Although YOLO has slightly lower detection accuracy than other detection methods, it is characterized by its high detection speed, and is expected to enable early detection from large images such as ortho and satellite images. YOLO has been implemented in several versions, from YOLOv1 to YOLOv7, but YOLOv5 was used in this study. The YOLOv5 (Glenn, 2020) used in this study has several models from which the network size can be selected (5s, 5m, 5l, and 5x), 5m was used in this study.

4. EXPERIMENTAL RESULTS

4.1 Disaster area detection using aerial images by UAV

We attempted to detect damaged areas using aerial images taken by UAVs at the actual disaster site. The flow of learning and detection is as follows. In addition, 80% of the decoded data, excluding images used for testing, was used as training data, and 20% as validation data.

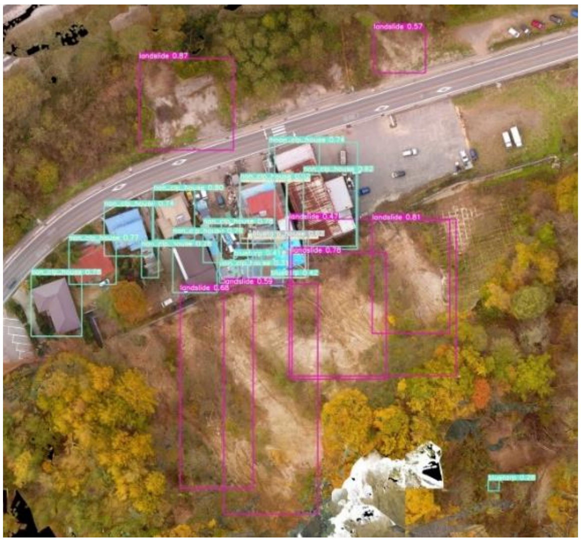

Fig. 1. Landslides detection result.

Fig. 2. Flood damage detection result.

1. Create training data by deciphering the damaged area from aerial drone images of the affected area.
2. Train YOLO models using the training data.
3. Detect disaster areas using ortho-mosaic images.
4. Training with batch size of 16 and the number of epochs is 500.

Detection results from orthomosaic images of landslides and flood damage area are shown in Figures 1 and 2, respectively.

In Figure 1, three landslides are detected. The large landslide in the lower left center of the image is detected as multiple landslides. One house covered with blue tarps was also detected, and the other blue tarps were correctly detected. There are 13 normal houses, which were also detected, but there are also two false positives.

In Figure 2, one flood damage location is detected in the vicinity of the bridge. However, the flood damage location in the lower part of the bridge was not detected. While most of the houses and blue tarps were detected correctly, some solar panels were incorrectly detected as houses.

The results in Figures 1 and 2 show that the model learned from the drone image train data can detect the affected area in the orthomosaic image. Next, as another disaster site, we obtained aerial photographs of the Azumagawa area of the 2018 Hokkaido earthquake from Geographical Survey Institute maps and attempted to detect landslides. The results are shown in Figure 3.

Fig. 3. Landslide detection result from 2018 Hokkaido Iburi Eastern Earthquake.

In Figure 3, there are several landslides, but only one landslide could be detected. The following factors may be responsible for the low detection rate.

- The training data used to create the model was based on landslides caused by typhoons, whereas the Hokkaido landslides were caused by earthquakes, resulting in different colors of exposed ground.
- Difference in the scale of the landslides.
- Difference in image resolution.

Therefore, we tested whether the addition of training data obtained from aerial images of the Hokkaido earthquake would enable detection. Using aerial images obtained from Geographical Survey Institute maps, 50 samples were deciphered and added to the training data and. The results are shown in Figure 4.

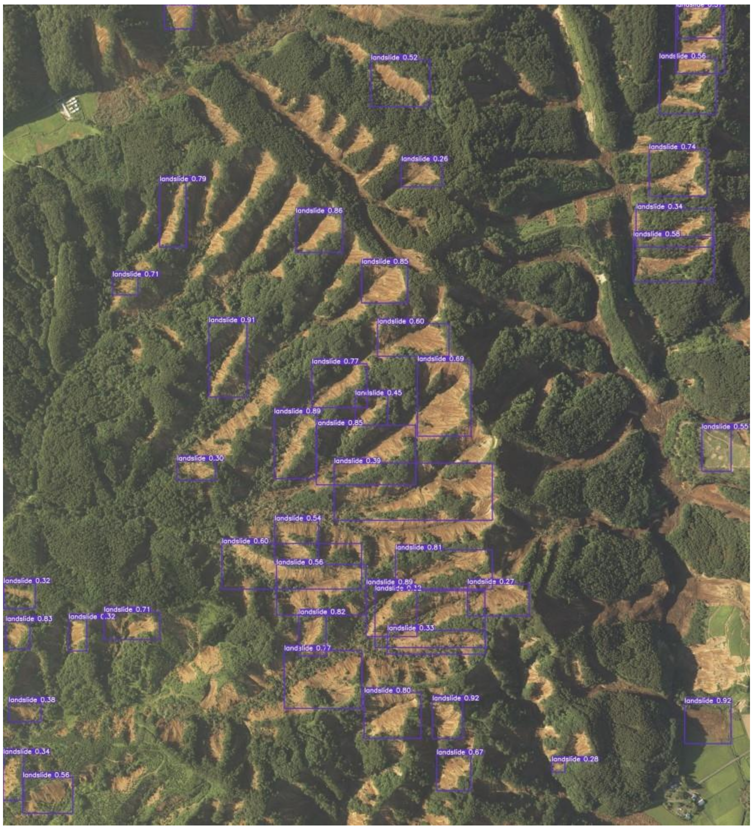

Fig. 4. Landslide detection result by the model using added 50 samples from Hokkaido earthquake.(Fig.3 is a part of Fig.4))

Figure 4 shows that the addition of training data improved the detection rate. The number of landslide detections increased from 1 to 43, and 1 false positive were found.

4.2 Disaster area detection using satellite imagery

With the aim of quickly identifying the occurrence of a wide range of disasters in the case of a large-scale disaster, we attempted to detect the landslides of the Hokkaido earthquake from satellite imagery. The acquired satellite imagery were taken on September 6, 2018, immediately after the earthquake, and on September 2, 2019, when the season was close to the time of occurrence and cloud cover was low. Each image was cropped to a size of 800x800 centered on the location of the landslides.

The September 2018 image was divided into two parts, upper and lower, and 12 landslides were decoded from the lower half and added to the training data, while the remaining upper half, as well as the September 2019 image, were used to testing. The results are shown in Figure 5.

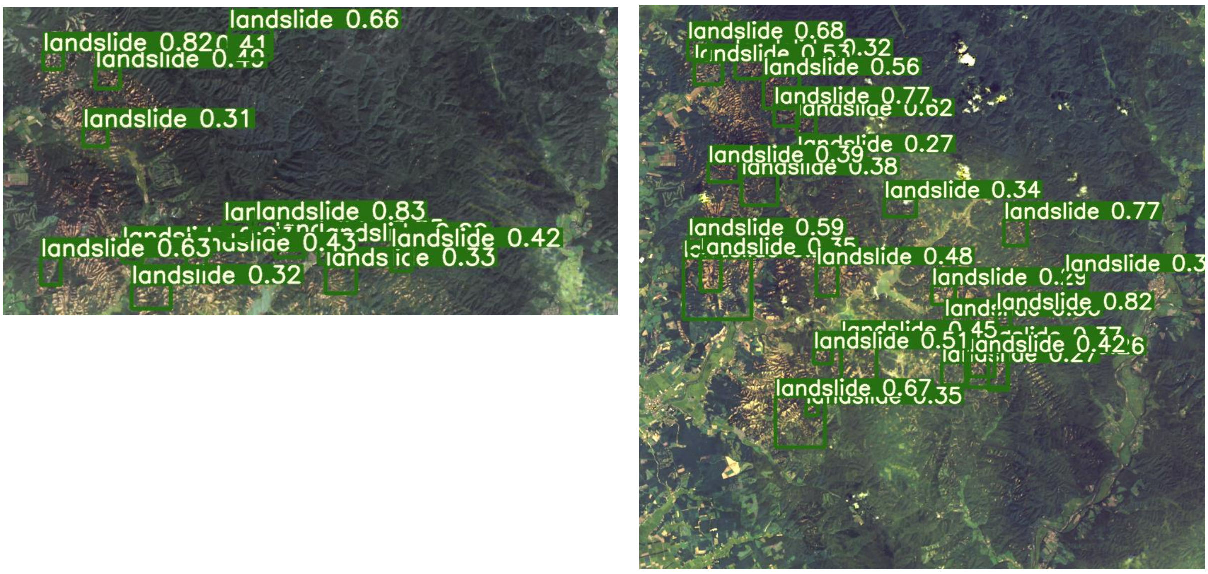

Fig. 5. Landslide detection results from satellite imagery by Landsat-8. 15 landslides were detected in the left image, the top half of the September 2018 image. 27 landslides were detected in the right image, the September 2019 image.

Figure 5 shows that 15 landslides were detected in the top half of the September 2018 image and 27 landslides were detected in the September 2019 image. Compared to visual decipherment, not all landslides were detected, but there were no false positives.

5. CONCLUSION AND DISCUSSION

In this study, we attempted to detect damaged areas (mainly landslides) with an object detection algorithm using UAV aerial images and satellite imagery of disaster-stricken areas. The model trained using drone aerial images taken in typhoon-stricken areas showed that the damaged areas can be detected from the orthomosaic images. However, the detection rate of landslides in other areas caused by different factors, such as earthquakes, was low.

Therefore, we added training data on earthquake-induced landslides, which showed an improvement in detection accuracy. The same was also confirmed for satellite imagery. Therefore, it can be said that the object detection algorithm is effective for the detection of disaster areas by providing appropriate training data according to the type of disaster area. Even for the same type of disaster detection, it is important to create training data considering the difference of occurrence factors such as typhoons and earthquakes, the difference of scale, and the resolution of the images.

The data deciphered in this study is biased in the number of samples among classes, so obtaining sufficient training samples for each class is an important problem. The future work is to construct a model that can detect a variety of disaster situations such as flood damage and building collapse in addition to landslides.

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