Method for Disaster Area Detection with Just One SAR Data Acquired on the Day After Earthquake Based on YOLOv8

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***Abstract*—Method for earthquake disaster area detection with just a single satellite-based SAR data which is acquired on the day after earthquake based on object detection method of YOLOv8 and Detectron2 is proposed. Through experiments with several SAR data derived from the different SAR satellites which observed Noto Peninsula earthquake occurred on the first of January 2024, it is found that the proposed method works well to detect several types of damages effectively. Also, it is found that the proposed method based on "Roboflow" and YOLOv8 as well as Detectron2 for annotation and object detection is appropriate for disaster area detection. Furthermore, it is possible to detect disaster areas even if just one single SAR data which acquired on the day after the disaster occurred because the trained learning model for disaster area detection is created through experiments.**

Keywords—SAR; YOLOv8; Detectron2; earthquake; disaster; disaster area detection; noto peninsula earthquake

I. Introduction

Sever damages have been occurred in Noto peninsula in Japan due to big earthquake hit on January first in 2024. The damages include landslides, big fires, collapse of buildings and houses, steep slopes, roads, etc. Such these damages can be detected from space with the satellite-based SAR data which allows observation in all weather conditions and day and night times. It is easy to detect the disaster areas by comparing two SAR data which area acquired on the day before and the after the earthquake.

There are two types of SAR satellites, constellation SAR and revisit orbital SAR. In general, the constellation SAR has narrow swath with fine spatial resolution characteristics while the revisit orbital SAR has relatively wide swath with comparatively poor spatial resolution, respectively. Therefore, it is not so easy to obtain two SAR data on the day before and the after the earthquake for the constellation SAR for interferometric SAR and coherency calculation. The method proposed here allows damage area detection with just the constellation SAR data which is acquired the day after the earthquake. SAR data gives information of land cover types so that the disaster areas, house burnt down by fire, slopes and mountainsides covered with vegetation that were reduced to bare land can be detected.

Sentinel-1 [1], operated by Europe, and ALOS-2 [2] (Its dataset [3]), operated by Japan, are both SAR satellites, but because the microwave wavelengths used for observation are different, the damage is seen differently. By taking advantage of this characteristic and combining the results of each analysis, we were able to classify the damage situation. The damage estimation map identifies areas where the ground surface has changed due to various causes associated with the earthquake, and where buildings such as houses may have been deformed. Possible causes of changes in ground surface conditions include ground displacement due to crustal deformation and strong shaking, flooding due to tsunamis, sediment inflow from slopes, and deformation of buildings. Damage to buildings includes various types of damage such as "washing away and collapse due to tsunami," "burning down due to fire," "collapse and roof tiles falling due to earthquake shaking," and "tilting due to liquefaction." This information includes secular changes such as expansions and renovations that occurred during the data observation period, and changes in the ground surface due to crustal deformation.

The purpose of this study is to clarify an effective method for disaster area detection with just one satellite-based constellation SAR data acquired on the day after earthquake. For object detection method, YOLOv8 [4] and Detectron2 [5] is used. YOLOv8 and Detectron2 is one of the effective object detection methods of which the damage areas are detected with learned AI models by using satellite-based SAR data through learning processes with an annotation process based on an instance segmentation of disaster areas. The method proposed here is based on the learned AI model, particularly YOLOv8 and Detectron2 of object detections. YOLOv8 is a state-of-the-art object detection and image segmentation model created by Ultralytics, the developers of YOLOv5 while Detectron2 is model zoo of its own for computer vision models written in PyTorch.

Research background and related research works are described in the following section followed by the proposed method. Then experiments are described followed by conclusion with some discussions.

[1] https://www.opengis.co.jp/htm/gamma/Sentinel-1_Download.html
[2] https://www.eorc.jaxa.jp/ALOS-2/img_up/jpal2_howto_insar.htm
[3] https://www.eorc.jaxa.jp/ALOS/jp/dataset/alos_open_and_free_j.htm
[4] https://github.com/ultralytics/ultralytics
[5] https://github.com/facebookresearch/detectron2

II. Research Background and Related Research Works

A. Research Background

The Noto Peninsula Earthquake is an earthquake that occurred at 16:10 on January 1, 2024, with the epicenter located 42 km northeast of Anamizu Town, Hosu District, on the Noto Peninsula, Ishikawa Prefecture, Japan (see Fig. 1). The earthquake had a magnitude (Mj) of 7.6 according to the Japan Meteorological Agency, and the depth of the epicenter was 16 km. The maximum observed seismic intensity was 7, which was observed in Wajima City, Ishikawa Prefecture, and Shiga Town, Hakui District.

To date, 236 people have been confirmed dead in Ishikawa Prefecture due to the Noto Peninsula earthquake on January 1st, and the whereabouts of 19 people are still missing. Damage has been confirmed to 43,766 homes as of the 28th of January, mainly in the Noto region, and as of January 28, approximately 3,300 homes remain without electricity and approximately 42,490 homes remain without water supply. Regarding water outages, Ishikawa Prefecture has clarified the outlook for each local government and says that the tentative restoration period will be from the end of February to the end of March in most cases, and in some cases, it will be from April onwards.

B. Related Research Works

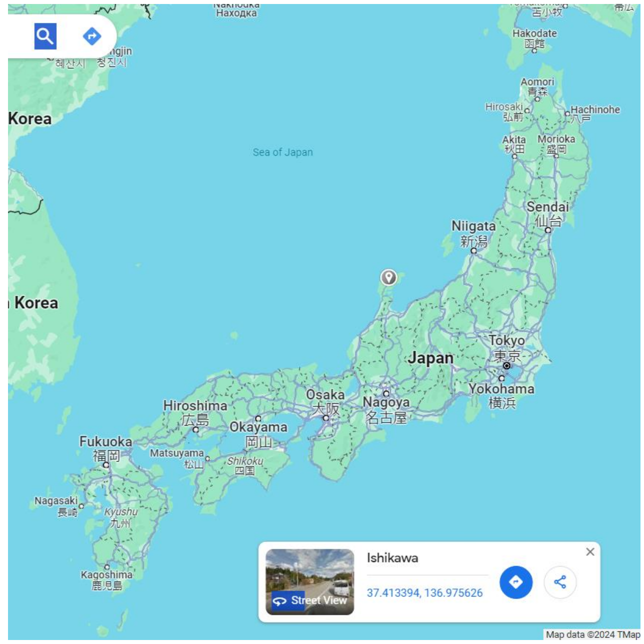
Application of the disasteretection method using SAR intensity images to recent earthquakes is introduced [1]. Also, building-disasteretection using post-seismic high-resolution SAR satellite data is investigated [2]. A comprehensive review of earthquake-induced building disasteretection with remote sensing techniques is published [3].

Earthquake disasteretection in urban areas using curvilinear features is attempted [4]. Meanwhile, earthquake damage visualization (EDV) technique for the rapid detection of earthquake-induced damages using SAR data is proposed [5]. On the other hand, a deep learning model for road disasteretection after an earthquake based on SAR and field datasets is proposed [6].

Probabilistic cellular automata-based approach for prediction of hot mudflow disaster area and volume is attempted [7]. Also, two-dimensional cellular automata approach for disaster spreading is proposed [8]. Meantime, probabilistic cellular automata-based approach for prediction of hot mudflow disaster area and volume is attempted [9].

New approach of prediction of Sidoarjo hot mudflow disaster area based on probabilistic cellular automata is tried [10]. On the other hand, cell-based GIS as cellular automata for disaster spreading prediction and required data systems is proposed and realized [11]. Meanwhile, sensor network for landslide monitoring with laser ranging system avoiding rainfall influence on laser ranging by means of time diversity and satellite imagery data-based landslide disaster relief is created [12].

Cell based GIS as cellular automata for disaster spreading predictions and required data systems is created [13]. On the other hand, flooding and oil spill disaster relief using Sentinel-1 and Sentinel-2 of remote sensing satellite data is attempted [14]. Convolutional neural network considering physical processes and its application to disaster detection is proposed [15]. More recently, a method for frequent high resolution of optical sensor image acquisition using satellite-based SAR image based on GAN (Generative Adversarial Network) for disaster mitigation is proposed [16].



(a) Ishikawa prefecture.

(b) Noto Peninsula.

Fig. 1. Noto Peninsula earthquake occurred in Ishikawa prefecture.

III. Proposed Method

A. Annotation

Kokusai Kogyo Co., Ltd. analyzes the changes in coherence using multiple satellite SAR observation data before and after an earthquake and identifies the area where building damage such as fire, liquefaction, and collapse/disaster to the earthquake occurred and the structure of the building. It has estimated the damage situation[6]. In accordance with their research report, disaster areas they found is shown in Fig. 2.

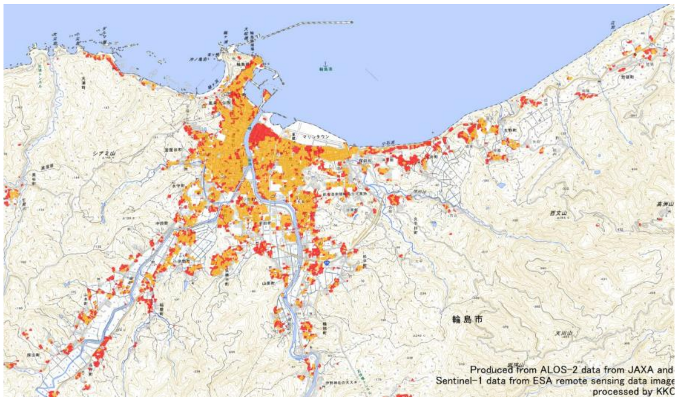


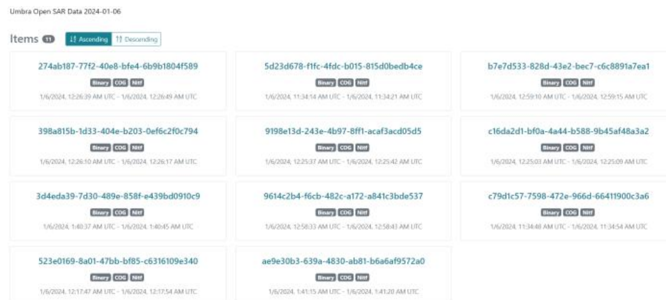
Fig. 2. Disaster areas found by Kokusai Kogyo Co. Ltd.

Meanwhile, The National Research Institute for Earth Science and Disaster Prevention publishes disaster situation data from satellite data from Synspective[7], Umbra[8], QPS Research Institute[9], Axelspace[10], JAXA[11], NASA[12], etc. through a disaster situation data site called Crossview[13]. This site is constantly adding image data obtained from satellite observations provided by satellite operating organizations. Optical satellites can capture images like cameras. Additionally, radar images are observed using electromagnetic waves that are invisible to humans and can be observed through clouds. Furthermore, thermal infrared sensors can observe high temperature regions. Among them, Umbra has released high spatial resolution SAR raw data, which clearly depicts the disaster situation. Therefore, by using these effectively, it is possible to understand the disaster situation, but the method for doing so is still not clear.

B. Proposed Approach

Learn with YOLOv8[14] and Detectron2[15] using the disaster area obtained from the Geospatial Information Authority of Japan's aerial photo interpretation, Planet Dove[16], and Pleiades Neo[17] for annotation. Roboflow[18] is used for annotation and augmentation as well as YOLOv8 and Detectron2 is used for creation of learned model for disaster areas.

The data used here is Umbra. The raw SAR data can be downloaded from the site[19] as shown in Fig. 3. 11 scenes of geotiff formatted Umbra SAR data were downloaded as shown in Fig. 3(a) while an example of downloaded Umbra SAR data is also shown in Fig. 3(b). The example of Umbra SAR data is a portion of the downloaded images of north part of the Noto Peninsula taken on the 6th of January 2024. The disaster areas of landslides, big fires, collapse of buildings and houses, steep slopes, roads, etc. are included in the scene. The backscattering intensity of the disaster areas of landslides, big fires, collapse of buildings and houses, steep slopes, roads, etc. shows relatively high because scattering components are gotten increased.



(a) List of the downloaded Umbra SAR data

(b) Example

Fig. 3. An example of the data used for disaster area detection.

IV. EXPERIMENTS

We compared estimates of landslide disaster areas based on aerial photographs from the Geospatial Information Authority of Japan with optical images. As a result, it was found that the shape of the actual disaster may be different, such as that the disaster area may not have exposed bare ground due to fallen trees, etc. as shown in Fig. 4(a).

After comparing the post-disaster optical images with Umbra's SAR data, we found that in Fig. 4(b), the disaster area was not visible in the SAR data due to radar shadows, so we needed to take a closer look. It was also found that the red frame was not visible, but the blue frame was visible. Although many other SAR data are available, Swath is narrow but has high spatial resolution, and the raw data can be downloaded for free, so we used only Umbra's raw data for training.

In Fig. 4(b), red and blue rectangles show that invisible and visible areas. Because the disaster area is not visible in the

[6] https://www.kkc.co.jp/disaster/2024/01/%E4%BB%A4%E5%92%8C%EF%BC%96%E5%B9%B4%E8%83%BD%E7%99%BB%E5%8D%8A%E5%B3%B6%E5%9C%B0%E9%9C%87/
[7] https://synspective.com/
[8] https://radiantearth.github.io/stac-browser/#/external/s3.us-west-2.amazonaws.com/umbra-open-data-catalog/stac/2024/2024-01/2024-01-06/catalog.json?.language=en
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[12] https://www.earthdata.nasa.gov/learn/backgrounders/what-is-sar
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[16] https://www.planet.com/our-constellations/
[17] https://www.airbus.com/en/space/earth-observation/earth-observation-portfolio/pleiades-neo
[18] https://roboflow.com/
[19] https://radiantearth.github.io/stac-browser/#/external/s3.us-west-2.amazonaws.com/umbra-open-data-catalog/stac/2024/2024-01/2024-01-06/catalog.json?.language=en

SAR data due to radar shadowing, it is necessary to take a closer look.

55 scenes of Umbra SAR data are used for training and augmentation. Also, five scenes are used for validation and three test scenes are used for test performances, respectively. These are shown in Fig. 5(a), (b) and (c), respectively.

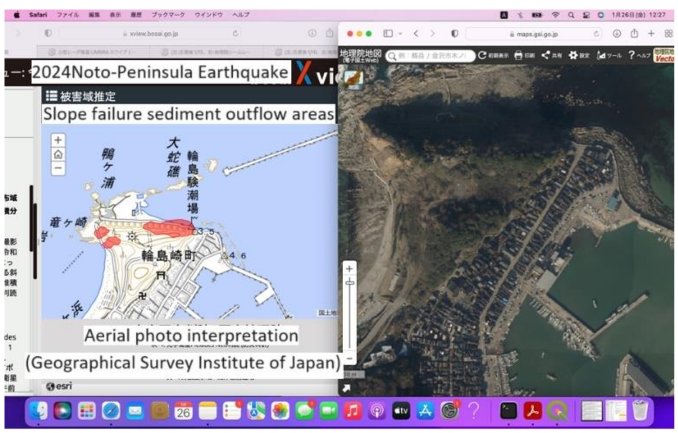
In comparison to learning processes between YOLOv8 and Detectron2, it is found that followings: There is a discrepancy between Umbra and the actual terrain, which is thought to be a problem with annotation accuracy. Road blockages may be detected. There are various types of actual disasters, such as landslides, debris flows, and landslides. Looking at the optical images, we found that although the affected area was large, there were some disasters where the ground was covered with fallen trees and was not visible on SAR. It is also possible that the vegetation has decreased in winter, making it difficult to recognize areas that have become bare ground.

There are also problems that cannot be recognized due to not only shadowing, but also foreshortening, layover, etc.

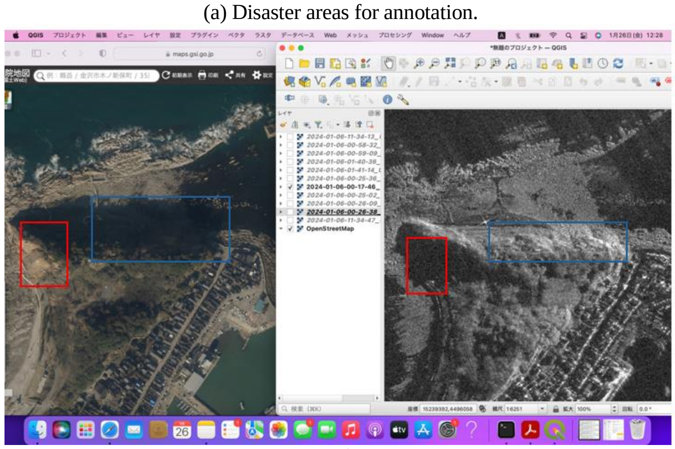
Fig. 6 shows the learning performance of YOLOv8 while that of Detectron2 is shown in Fig. 7.

Fig. 8(a) and (b) shows the detected disaster areas at the number of epochs of 300 and 500, respectively. The number of epochs for Detectron2 is 1500 while that of YOLOv8 is 1000, respectively. The learning performance of YOLOv8 can be shown in the form of the loss functions of the training and the validation for box, segmentation, classification and DFL which area shown at the left side of Fig. 6. Meanwhile, that of Detectron2 evaluation results are displayed as logs and indicators. Common evaluation metrics include mean object detection accuracy (mAP) as well as precision and recall which are shown in Fig. 7. Total loss function is gradually decreased in accordance with the number of iterations and is stable at more than 1500 of iterations for Detecrton2.

Box, segmentation, classification and DFL loss functions of training and validation are shown for YOLOv8 learning performance while Metric mAP50, mAP50/95 are shown for Detectron2 learning performance, respectively. Where, mAP50 denotes mean average accuracy calculated with an intersection over union (IoU) threshold of 0.50. This is a measure of the accuracy of the model considering only "simple" detections while mAP50-95 denotes mean average accuracy calculated at various IoU thresholds from 0.50 to 0.95. A comprehensive view of model performance at different detection difficulty levels can be understood. Segmentation and classification show relatively good training and validation performances box loss function is not so good performance. Therefore, it is not so good bounding box cannot be determined in particular for the validation.



(a) Disaster areas for annotation.



(b) Optical sensor image and SAR image used for YOLOv8 and Detectron2 learning process.

Fig. 4. Data used for annotation and learning process.

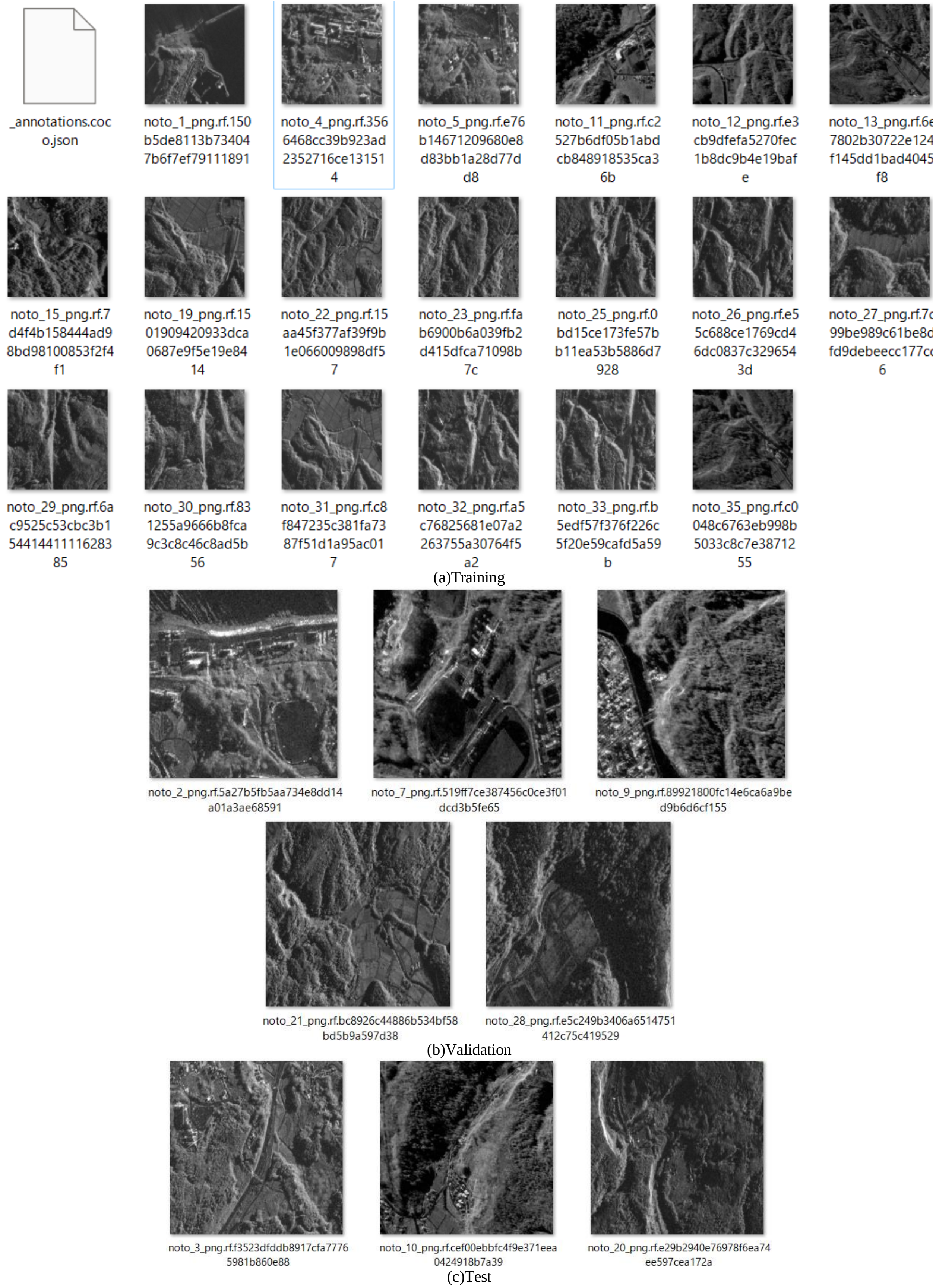


Fig. 5. Data used for training, validation and test of learning performance evaluations.

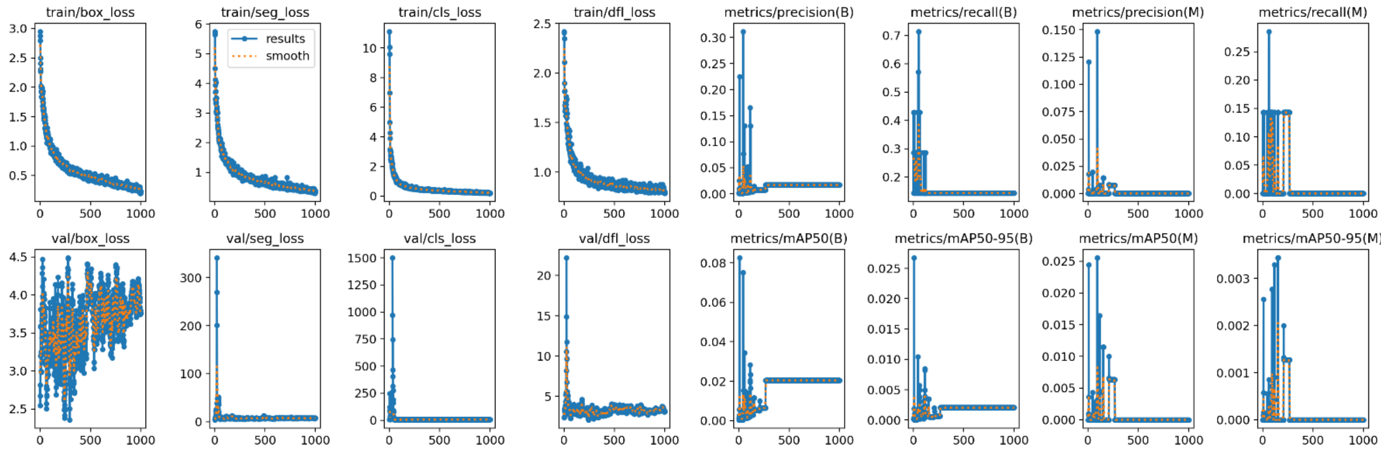


Fig. 6. Learning performance of YOLOv8 for damage area detection.

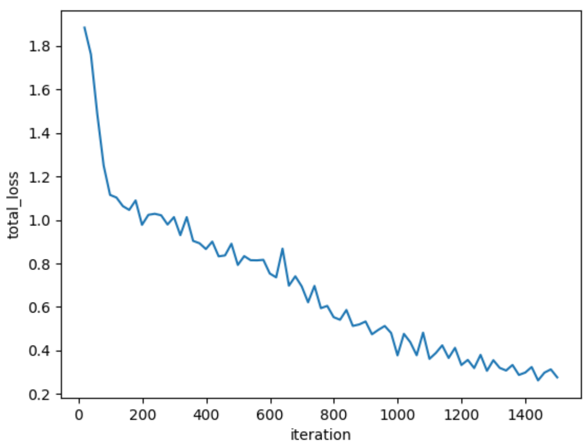
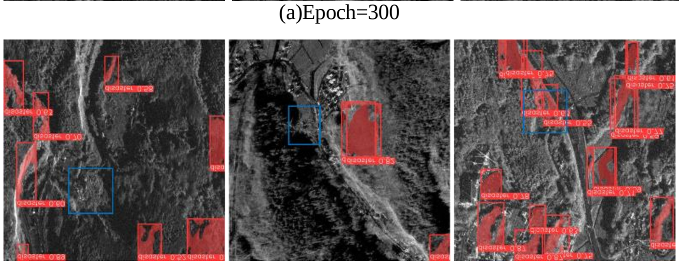


Fig. 7. Total loss function of Detectron2

(a)Epoch=300



(b)Epoch=500

Fig. 8. Detected disaster areas with Umbra SAR data through learning process with YOLOv8 and Detectron2.

In comparison of the detected disaster areas between epoch=300 and 500, it is found that the number of detected disaster areas for epoch=300 is smaller than that for epoch=500. Also, it is found that the number of detected disaster areas are almost same for the epoch>500. Furthermore, the detected disaster areas are almost matched to the annotated areas and visual perceptions. Therefore, epoch=500 would be enough for the learning process.

V. CONCLUSION

Method for earthquake disaster area detection with just a single satellite-based SAR data which is acquired on the day after earthquake based on object detection method of YOLOv8 and Detectron2 is proposed. Through experiments with several SAR data derived from the different SAR satellites which observed Noto Peninsula earthquake occurred on the first of January 2024, it is found that the proposed method works well to detect several types of damages effectively. Also, it is found that the proposed method based on Roboflow and YOLOv8 as well as Detectron2 for annotation and object detection is appropriate for disaster area detection.

Furthermore, it is possible to detect disaster areas even if just one single SAR data which acquired on the day after the disaster occurred by using the trained model built here. Using the truth data of disaster areas which are derived from aerial photo interpretations and space-based SAR imagery data, trained learning model is created with YOLOv8 and Detectron2. This model can be applicable to detect disaster areas by using a single SAR imagery data. It is beneficial to prevent secondary disasters and to plan for disaster recovery. In order for that, a transfer learning process is required with the acquired SAR imagery data which is acquired just after disaster occurred.

FUTURE RESEARCH WORKS

This paper would be the first preliminary paper which deals with the Noto Peninsula earthquake which occurred on 1st of January 2024. Object detection-based method for disaster area detection would be original for grasp earthquake disaster situation. Further study is required for improvement of the accuracy of disaster area detection with the other methods not only Roboflow and YOLOv8 as well as Detectron2, but also EfficientNet and the others.

Acknowledgment

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