Semantic Segmentation of Landsat images for Detection of Wildfire-damaged Areas

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ABSTRACT: In this study, we conducted to detect the damaged areas caused by forest fire through satellite image data and deep learning. There are many studies to detect the damages based on hyper-spectral aerial images, satellite images, vegetation index and factors affecting the forest environment. However, we tried to make it possible to apply more accurate and various forest disaster events by combining the deep learning technology. We collected Landsat-5 and Landsat-8 satellite data and used U-net which is the Semantic Segmentation model. Also, we tried to increase the accuracy of training by using NDVI(Normalized Difference Vegetation Index), NDWI(Normalized Difference Water Index), and FWI(Fire Withering Index) as the input data, and tried to verify the applicability to other forest disasters and to prove that deep learning is a useful tool for segmentation and object recognition of satellite image data.

1. INTRODUCTION

Forests are important role in creating the atmosphere of the earth, and by absorbing and fixing huge amounts of carbon dioxide, the earth can maintain an appropriate atmospheric temperature. According to various domestic and international research results, forests perform functions such as reporting of life resources, prevention of desertification, and adjustment of micro climate. Especially, in Korea, 64% of the nation is made up of forests, among them, coniferous forests account for 43%, so the risk of forest fires is high. In addition, forest pest damage and hail damage have increased interest in forest disasters.

2. DATA

2.1 Satellite Images

Satellite images used for forest fire detection were obtained from Landsat 5 TM Laevel2 data and Landsat 8 OLI / TIRS Level-2 data provided by the USGS(United States Geological Survey). Landsat series has a 30m spatial resolution and is widely used in the world in that data can be freely provided. In addition, Level 2 data is useful because Surface Reflectance data is available in all bands except Thermal bands and Panchromatic bands without correction. In the case of the images used in this study, the regions with damage area of 10 hectare(ha) or more was selected for 16 years (2003 ~ 2018) by referring to the forest fire damage book provided by the Korea Forest Service, and we tried to use the data within 3 months from the damaged date. However, in the process of receiving the image, the damaged area is covered by the cloud, or in the winter period, the area is indistinguishable due to the shadow of the mountain range, and there is no image of the region and the damaged date. As a result, 48 images were available in this study. Input image size was set to 96 x 96 to reduce errors caused by surrounding pixel values as much as possible. In case of the true label, we used to QGIS software to create the true raster label using RGB true color image and bands combination image of R, NIR, and G.

2.2 Data preprocessing

In deep learning research, preprocessing of input data is an important step in model training process. Min-max normalization is a process that converts the range of pixel values of the image into the range of 0-1, and standardization is process that transforms the distribution of data into Gaussian distribution by converting the mean to 0 and the standard deviation to 1 using the mean and standard deviation of the images. The reason for this preprocessing is to improve learning speed and solve local optimization problems. In this study we applied standardization on the input image, and we used to R, NIR, G, NDVI, NDWI, FWI(Park, 2019) as input data

3. METHODOLOGY

3.1 Semantic Segmentation

Semantic Segmentation is a method of recognizing objects in the spatial context when segmenting an image by classifying associating each pixel of image. Typical segmentation models include FCN (Long, 2015), Unet (Ronneberger, 2015) and SegNet (Badrinarayanan, 2016). Semantic segmentation eliminates Fully Connected Layer and organizes all layers into convolution layers to increase computational efficiency and utilize spatial contextual information from each pixel to prevent loss of spatial information and to recognize what objects are and where they are. In this study, we used U-net models for damaged area detection.

4. RESULT & CONCLUSION

The input data was 800 images through data augmentation, and 10 cross-validation sets were created, each with 80 validation and 80 test sets. After dividing the all dataset into 10 folds, we compared the results for the epochs 300 and 500 and batch sizes 30 and 50. The optimizer uses 'Adam' and the loss function uses 'Binary cross entropy'. The learning rate was set to 0.0001. As a result, the accuracy was higher at 300epochs and 30 batch sizes, and the accuracy in each fold is shown in the table below. There is also a less accurate fold, which can be seen to be less accurate due to areas such as urban areas, roads and rivers around the damaged areas. In all other cases, a model with about 90% accuracy was obtained. Since the last activation function of the layer is sigmoid, the output of the model is 0 ~ 1 probability value, and it is easy to compare with the correct label when it is rounded up to 0.5 and expressed as 0 and 1 as shown in round 1 ~ 4 in the figure below. This study uses the deep learning image recognition to compensate for the limitations of the existing spectral characteristics based forest fire damage detection research and to detect the damage more accurately and quickly. So we believed that this model will be able to construct suitable for the detection of damaged areas through large data and research under various conditions. In the future, we will continue to build more accurate models by collecting fire damage data and generating training images for model optimization.

Table 1. result of u-net model 10-fold cross validation in 300epoch, 30batch size

Fold name	Accuracy	Precision	Recall	F1 score
Fold1	0.859	0.725	0.643	0.682
Fold2	0.924	0.749	0.782	0.765
Fold3	0.905	0.576	0.764	0.657
Fold4	0.866	0.785	0.688	0.733
Fold5	0.630	0.896	0.346	0.499
Fold6	0.917	0.701	0.842	0.765
Fold7	0.902	0.561	0.791	0.657
Fold8	0.862	0.684	0.704	0.694
Fold9	0.642	0.908	0.377	0.533
Fold10	0.755	0.853	0.492	0.624

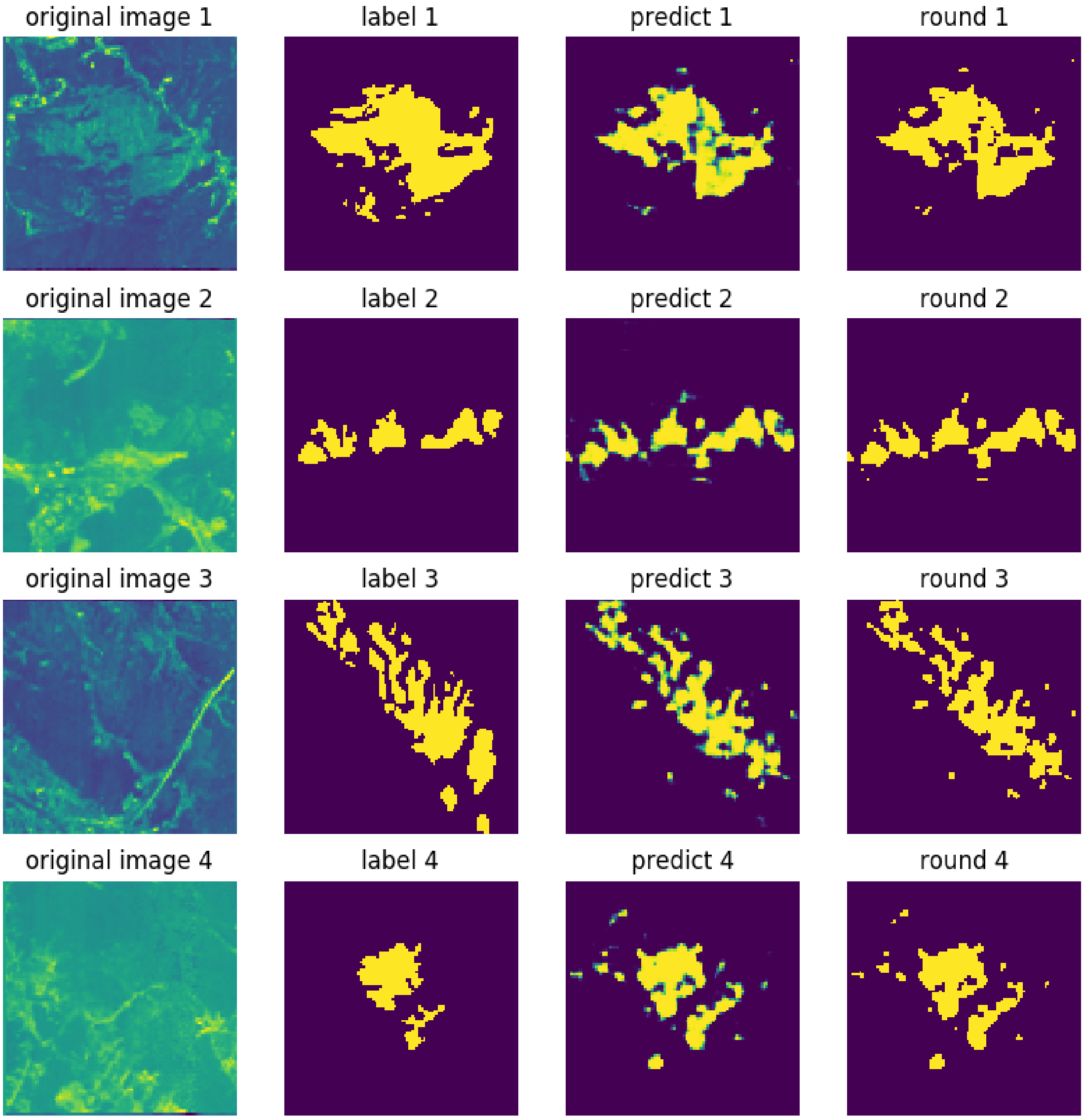

Figure 1. predict images of u-net model

5. REFERENCE

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