Land Cover Classification

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Video: https://youtu.be/LXlAwea2mXw
Code: link

ABSTRACT

During the late 20th and early 21st centuries, rapid and unchecked population growth, together with economic and industrial development, particularly in emerging nations, have multiplied the rate of land-use/land-cover change. Examining the accuracy of land-use/land-cover mapping is necessary in order to determine potential future uses of earth observations since quantitative assessment of changes in land-use/land-cover is one of the most effective ways to comprehend and manage land transformation. In this article, we have taken a kaggle dataset which is obtained from the Land Cover Classification Track in DeepGlobe Challenge. We investigate the use of the MA-Net model on the dataset with data augmentation and observe the accuracy of 99.83% which is better than the state of the art methods.

INTRODUCTION

Recent developments in remote sensing technology and the rapidly expanding amount of remotely sensed data have fundamentally altered how we view the planet.The classification of land cover and subsequent monitoring of changes are two important uses of Earth observation.The mapping of the Earth's land cover is very useful for many purposes, including environmental monitoring, agricultural and urban planning, the forecasting of hazardous events and natural disasters, etc.

The examples and elements of land-use/land-cover have been planned utilizing different strategies, including both ordinary earthly planning and satellite-based planning. Earthly planning, likewise alluded to as a field overview, is an immediate technique for planning that permits the guide to be created at various sizes and consolidate data with different levels of accuracy, however it requires many individuals and is costly concerning both time and cash. Also, planning might be inclined to subjectivity.Then again, the planning of land use and land cover in view of satellite and ethereal photography is more reasonable, spatially expansive, multi-worldly, and efficient.

The objective of this task is to improve profound learning approaches for land cover planning in remote detecting and to recognize total or halfway answers for a portion of the significant issues with programmed remote detecting information examination and understanding.

RELATED WORKS

Many people worked on land cover classification dataset using different Machine Learning approaches. Among several approaches, Lu Htoo Kyaw used UNet++ [4] to solve this classification problem. Rost [5] used resnet34, inceptionv3 and vgg16 to generate mask for land cover classification that indicates the positions of the categories of the land cover. Moreover, Yao Li and Luo Chen [6] used Resnet-101 to consider land cover classification as a remote sensing image segmentation problem. However, meeting expectations in terms of various metrics is challenging. We examine the effect of the MA-Net model on various metrics for land cover classification.

METHODS

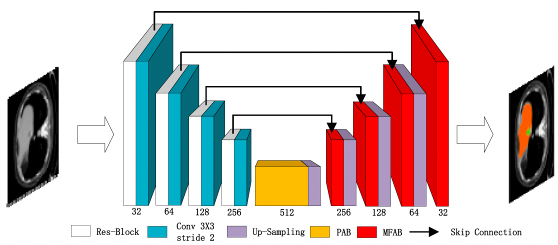


Fig. 1: Architecture of MA-Net [2]

Complete architecture of MA-Net is shown in Fig. 1. The self-attention mechanism is used in the MA-Net. Two blocks based on self-attention mechanisms are used to capture spatial and channel dependencies of feature maps. One is Position-wise Attention Block (PAB), and the other is Multi-scale Fusion Attention Block (MFAB). The PAB is used to obtain the spatial dependencies between pixels in feature maps by a self-attention mechanism manner. The MFAB is used to capture the channel dependencies between any feature maps by applying the attention mechanism. Channel dependencies of both high-level feature Maps and Low-level feature maps are considered. The channel dependencies of high-level and low-level feature maps are fused in a sum manner, which aims to obtain rich Multi-scale semantic information.

RES-BLOCK

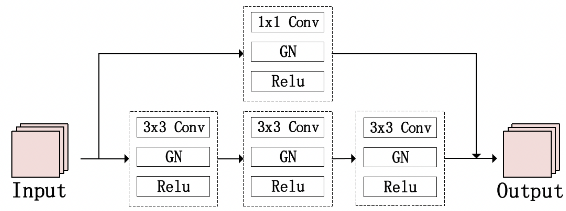


Fig. 2: Res-Block

There are three 3x3 convolution blocks and one residual connection to capture high-dimensional feature information. The 1x1 Conv is to control the number of input channels. Instead of batch normalization, group normalization [3] is used to avoid performance degradation of the model.

POSITION-WISE ATTENTION BLOCK

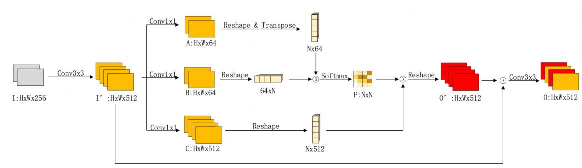


Fig. 3: The Position-wise Attention Block (PAB)

PAB is used to capture the spatial dependencies between any two position feature maps.

MULTI-SCALE FUSION ATTENTION BLOCK

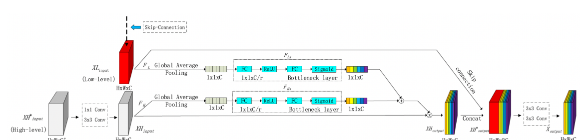


Fig. 4: Multi-Scale Fusion Attention Block

Multi-scale Fusion Attention Block (MFAB) is used to extract the interdependence among feature channels via combining the High and Low-level feature maps. The High-level features have rich semantic information of image and the Low-level features from Skip-Connection have more edge information. The Low-level features are used to recover the details of images.

LOSS FUNCTION

The Dice loss function can mitigate the imbalance problem of background and foreground pixels. However, it only pays attention to the accuracy rate in the training process. Therefore, a weighted loss function is used to optimize the MA-Net. The combination of cross- entropy and Dice is used as the final loss function in MA-Net.

$$L_{loss} = -\frac{1}{N}\sum\nolimits_{i=1}^{N}(\alpha y_i \log p_i + \beta \frac{y_i p_i}{y_i + p_i})$$

where y_i and p_i denote the ground truth and the predicted feature map, and N denotes the batch size. Two hyperparameters alpha and beta are used to control the effect of the weighted loss function.

EXPERIMENTS

Datasets

We have used the land cover dataset [1] that contains a collection of 1949 satellite images. This dataset is used to detect areas of urban, agriculture, rangeland, forest, water, barren, and unknown. There is a mask for each of the images (Fig. 5) which indicates the position of the categories of land cover.

Image Mask

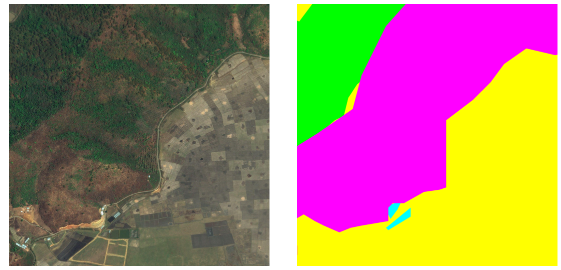


Fig. 5: Sample image and mask

There are 7 classes in the dataset such as urban land, agriculture land, rangeland, forest land, water, barren land and unknown (Fig. 6). Each class label has a different color code.

	name	r	g	b
0	urban_land	0	255	255
1	agriculture_land	255	255	0
2	rangeland	255	0	255
3	forest_land	0	255	0
4	water	0	0	255
5	barren_land	255	255	255
6	unknown	0	0	0

Fig. 6: Class labels and color codes

Settings

Hyper parameters and other settings we used in our experiment are given in the following table 1.

Table 1: Parameter setting

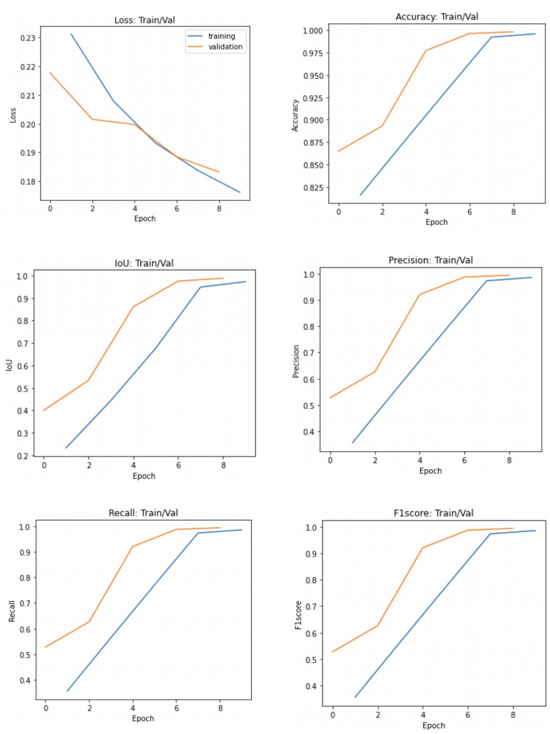
Name	Value
Image Size	320
Batch Size	16
Epochs	5

RESULT AND DISCUSSION

Our experiment shows that the MAnet model can provide outstanding performance in terms of accuracy, IoU, precision, recall and F1 score on land cover dataset which are better than Unet++ (Table 2)

Table 2: Test performance of MA-Net

Metric	Score of Unet++ [4]	Score of **MA-Net** [2]
Loss	0.1799	**0.1776**
Accuracy	0.9967	**0.9983**
IoU	0.9780	**0.9894**
Precision	0.9887	**0.9942**
Recall	0.9887	**0.9942**
F1 score	0.9887	**0.9942**



CONCLUSION

The purpose of this study was to evaluate the MA-Net model's accuracy for mapping land classification using satellite images.
After performing MA-Net method, it can be concluded that MAnet method can provide outstanding performance in terms of accuracy,IoU, precision, recall and F1 score on land cover dataset. It is visible that accuracy is 99.83%, IoU is 98.94%, Precision, Recall, F1 score are 99.42%

Reference

[1] Demir, Ilke, et al. "Deepglobe 2018: A challenge to parse the earth through satellite images." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2018.

[2] T. Fan, G. Wang, Y. Li and H. Wang, "MA-Net: A Multi-Scale Attention Network for Liver and Tumor Segmentation," in IEEE Access, vol. 8, pp. 179656-179665, 2020, doi: 10.1109/ACCESS.2020.3025372.

[3] Wu, Yuxin, and Kaiming He. "Group normalization." Proceedings of the European conference on computer vision (ECCV). 2018.

[4] LU HTOO KYAW ‘Landcover ClassificationUNet++’https://www.kaggle.com/code/luhtookyaw/landcover-classification-unet

[5] Rost, ‘DeepGlobe land cover classification’https://www.kaggle.com/code/rostekus/deepglobe-land-coverclassification/notebook

[6] Yao Li and Luo Chen, deepglobe land cover classification with deeplabv3plus ’https://github.com/GeneralLi95/deepglobe_land_cover_classification_with_deeplabv3plus