

CS 230: Image Segmentation & Object Detection of Lunar Landscape

Youtube. Link: <https://youtu.be/P1EmjuQdJ2s>

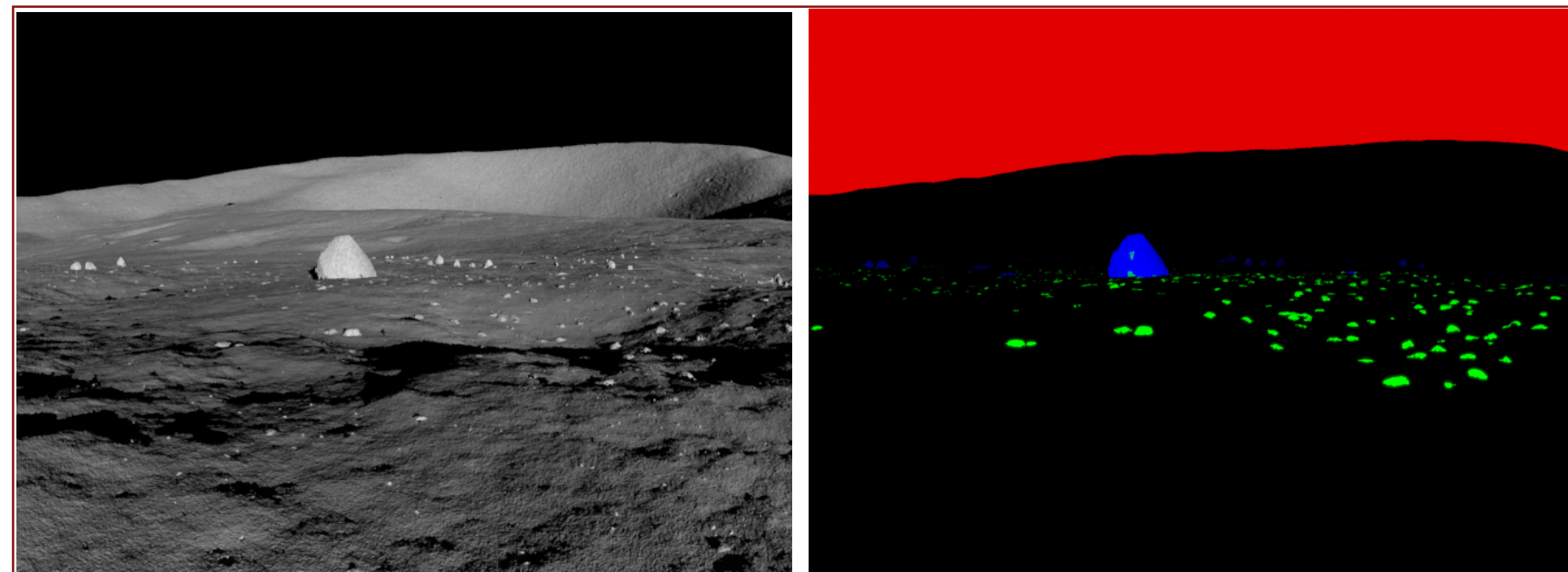
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CS Department

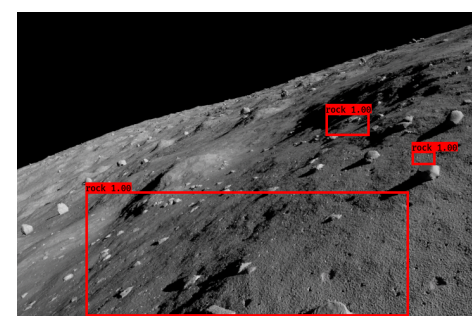
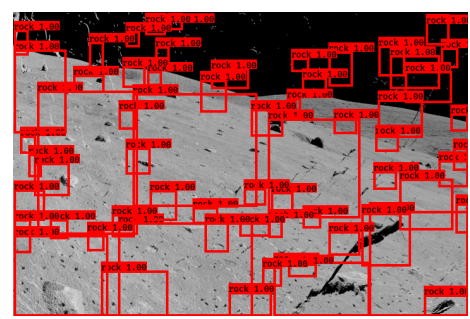
Introduction and Motivation



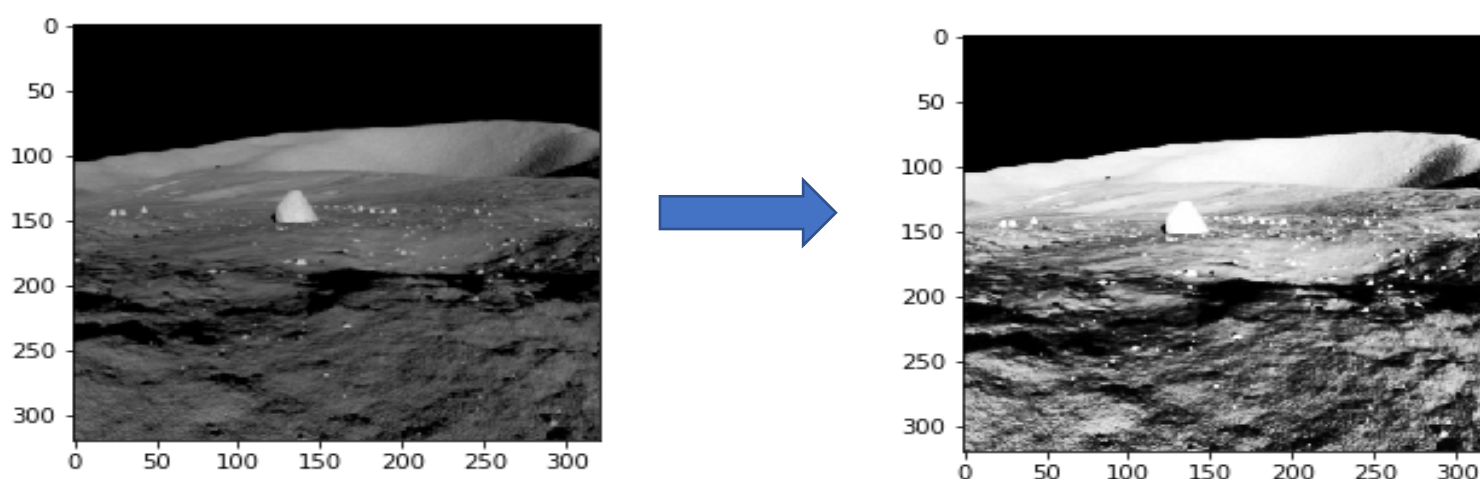
- Use the synthetic image (left) and segmentation (left) to train model
- Segment the synthetic lunar landscape
- Segment the real lunar landscape
- To see the possibility of lunar auto-driving

Dataset and Preprocessing

- Ishigami Laboratory group of Keio University: Artificial Lunar Landscape data set
- 9700 images
- Training Set: 6400
- Validation Set: 2000
- Eye balling defect images and rock labels for YOLO, e.g.



- Increase the contrast ratio of inputs:

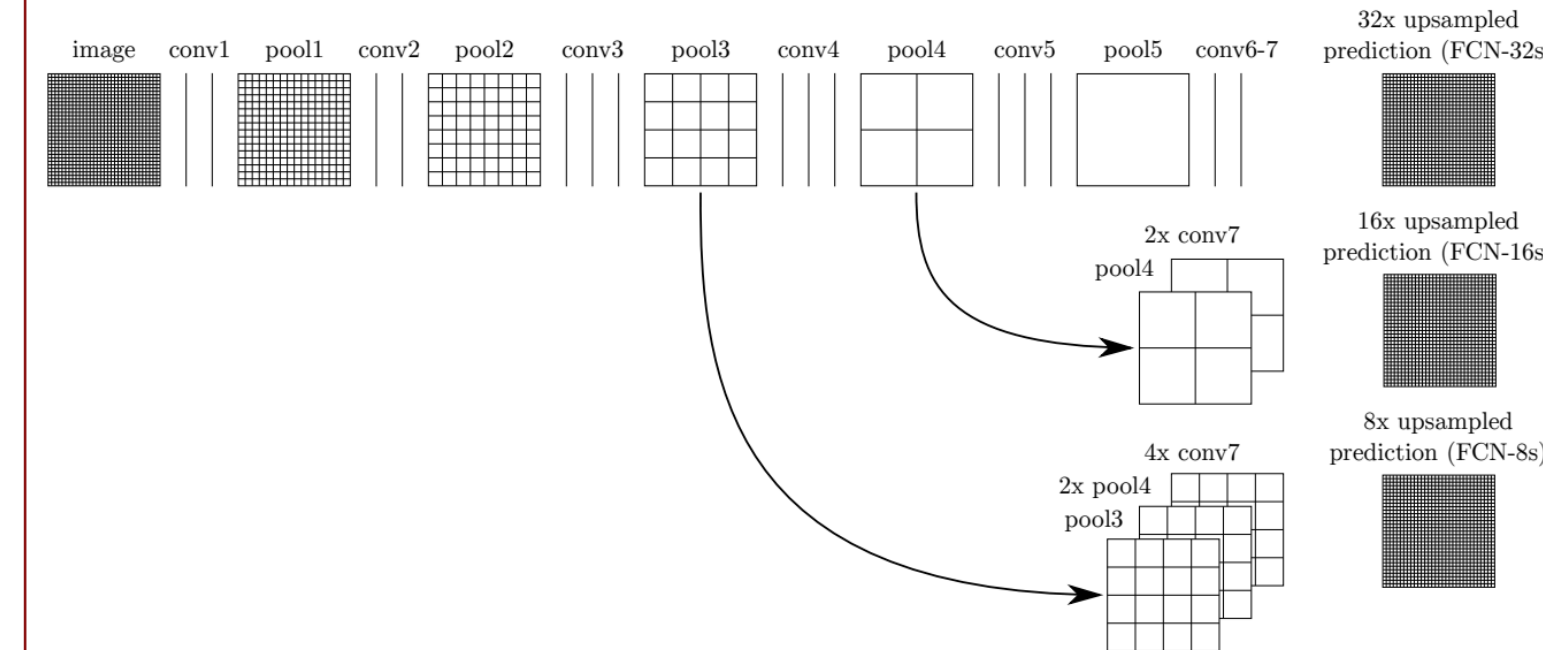


Model

YOLOv2

- Trained with YOLOv2 pretrained weights (full YOLO)
- Learning rate: 0.0001
- Optimization: Adam
- Anchors: 5 anchor boxes
- Grids: 13×13

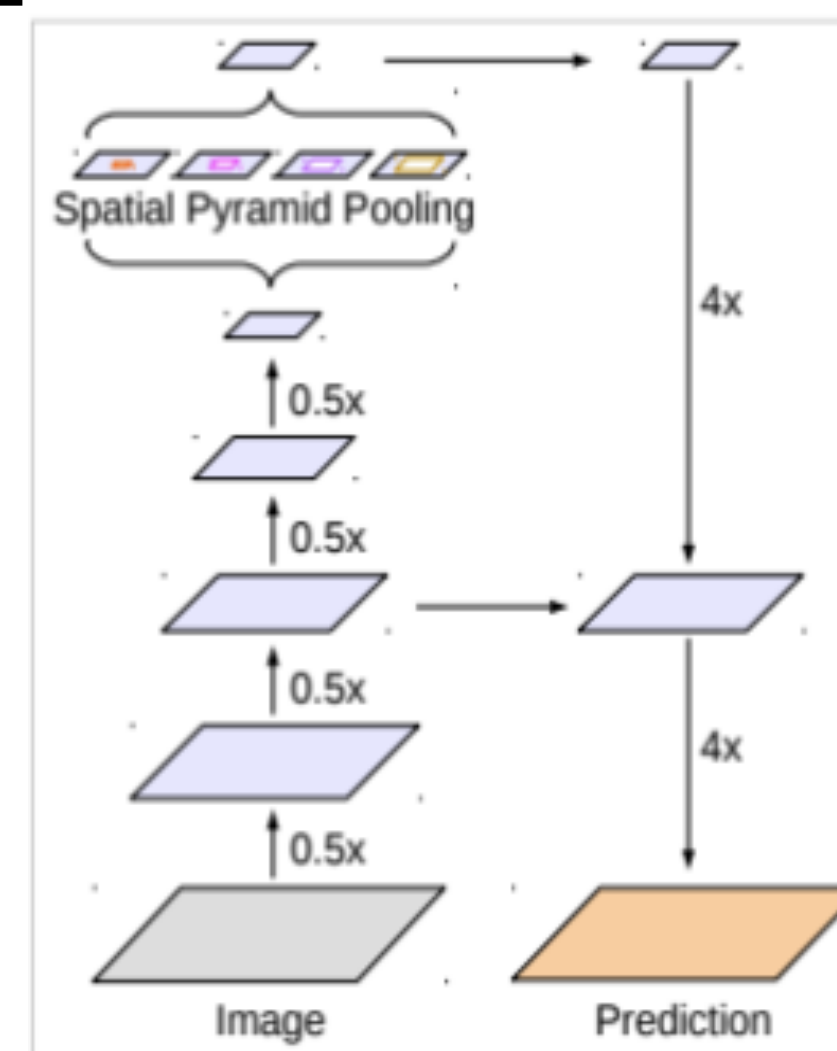
FCN-8S



- Trained from VGG-16 layer 15
- Learning rate: 0.0005
- Optimization: Adam

Deeplabv3+

- Learning rate: 0.0005 and then 0.0007 to overcome local minimum
- Optimization: Adam



Result and Comparison

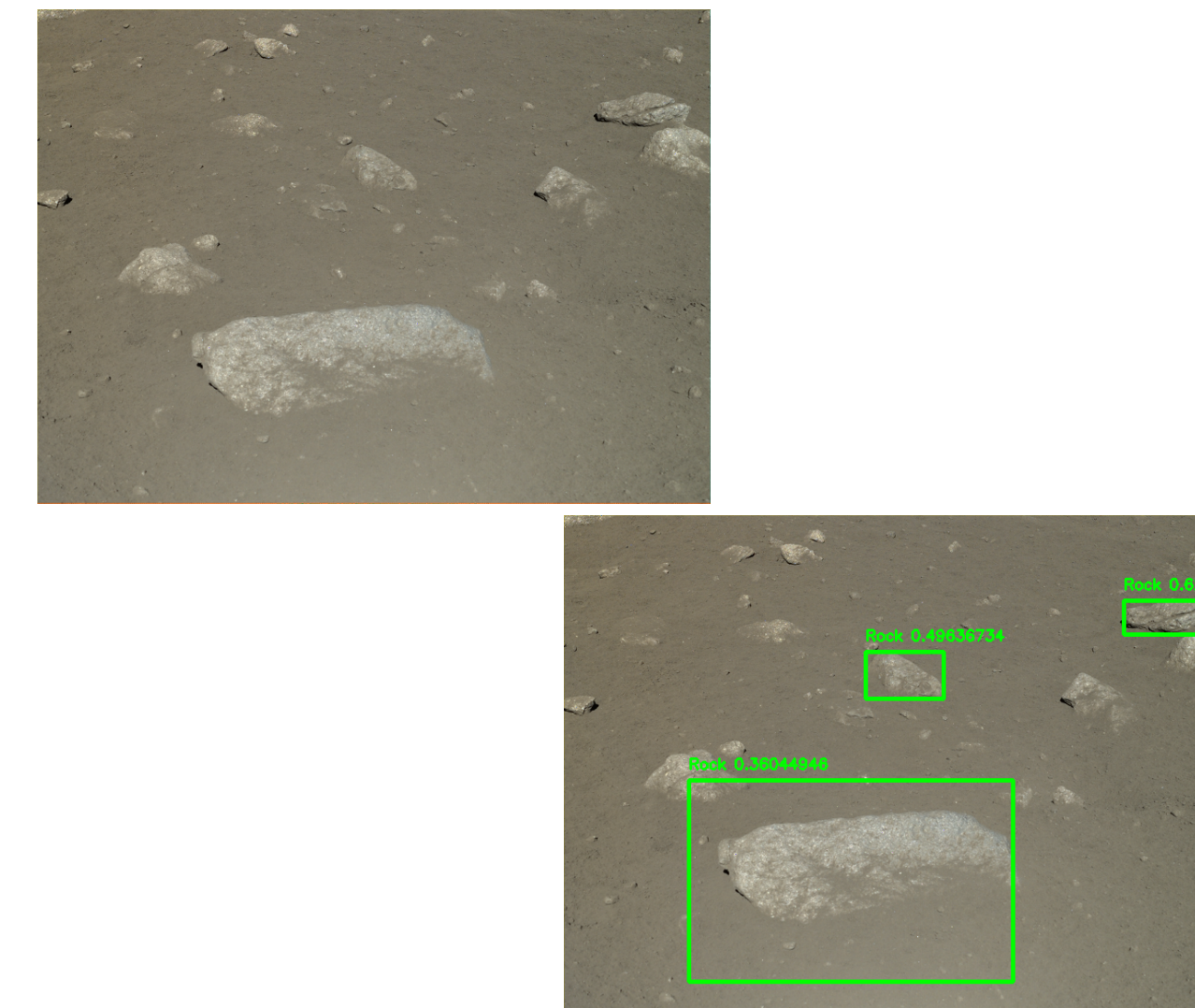


Figure 1: YOLOv2 rock detection on real lunar surface image

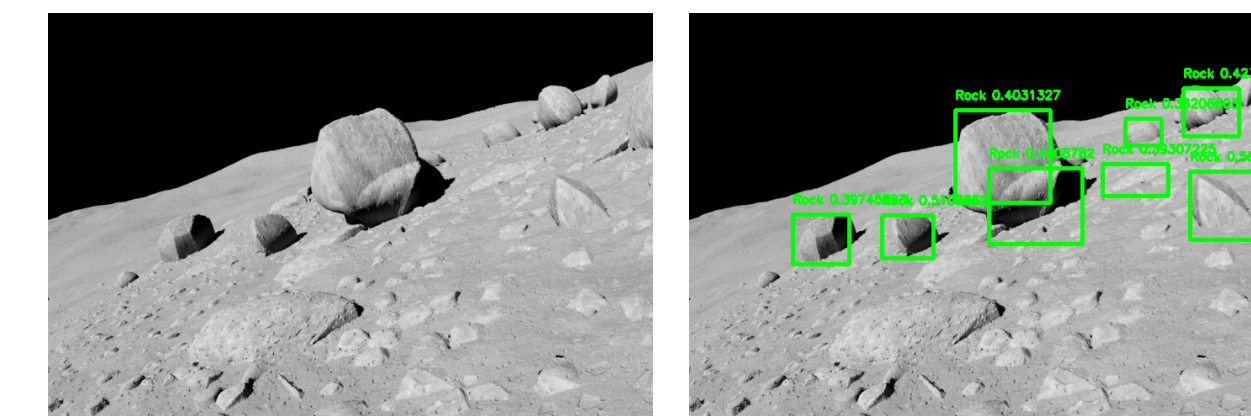


Figure 2: YOLOv2 rock detection on synthetic lunar surface image (mAP: 63.4%)

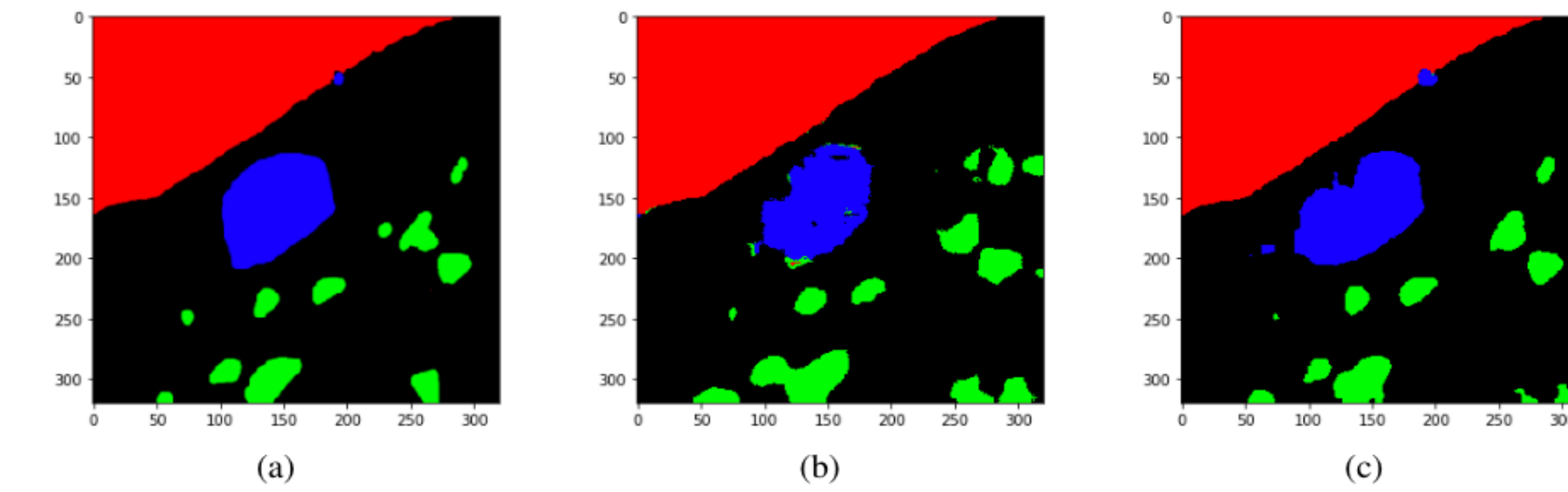


Figure 3: FCN and Deeplab comparison on validation image set of synthetic landscapes. (a) Cleaned ground truth; (b) FCN-8s prediction; (c) DeeplabV3+ prediction.

Model	final loss	Table 1: Results of FCN-8s and DeeplabV3+		
		Pixel-wise Accuracy	MeanIOU of training	MeanIOU of validation
FCN-8s	0.7666	0.9699	0.8829	0.8275
DeeplabV3+	0.08302	0.9728	0.8358	0.8232

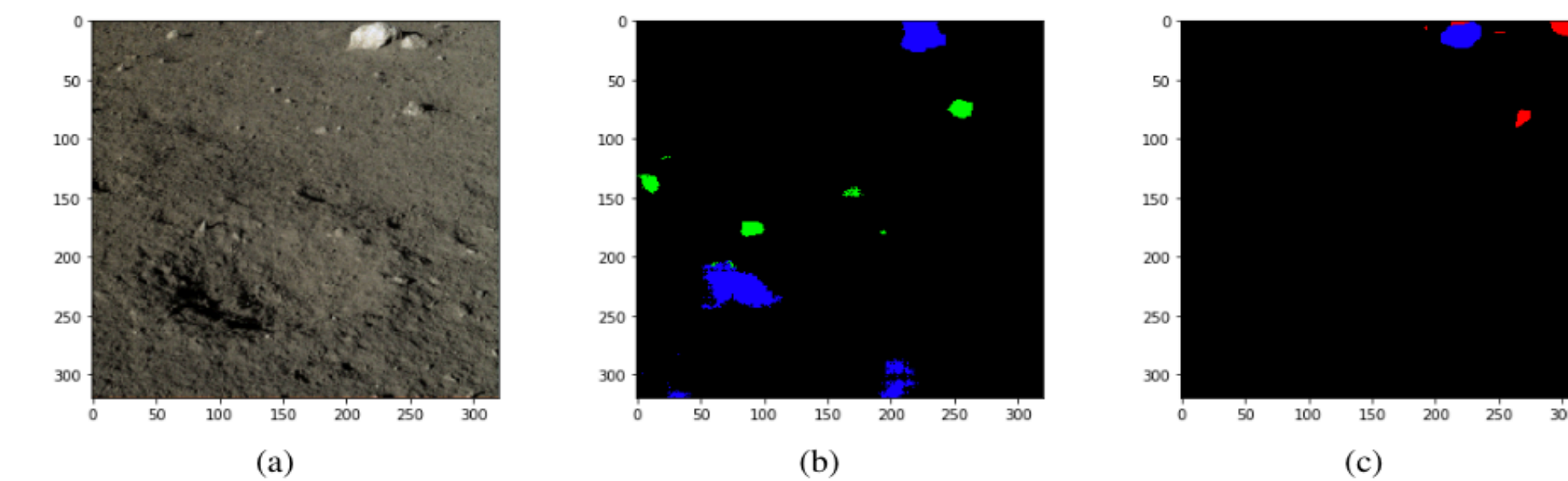


Figure 4: FCN and Deeplab comparison on real moon surface. (a) Cleaned ground truth; (b) FCN-8s prediction; (c) DeeplabV3+ prediction.

Future Improvement

- More realistic synthetic lunar surface will help a lot.
- Data augment the synthetic image and make it more like the real one.
- Improve data label and use data from different distributions

Reference

1. S Ghosh, N Das, I Das, and U Maulik. Understanding deep learning techniques for image segmentation. ACM Computing Surveys (CSUR), 52(4):1–35, 2019.
2. J Redmon and A Farhadi. Yolo9000: Better, faster, stronger. arXiv 2016. arXiv preprint arXiv:1612.08242.
3. J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015.
4. L. Chen, G. Papandreou, F. Schroff, and H. Adam. Rethinking atrous convolution for semantic image segmentation. arXiv preprint arXiv:1706.05587, 2017.