Lunar Surface Image Segmentation



December 12, 2022
George Washington University
Machine Learning II - DATS_6203_10
GitHub Repo





Going to the Moon!!

 Tasked to help land a lunar lander on the surface of the moon

- Many factors to consider in finding a safe landing location
 - Be nice to not crash into rocks

Can we use ML/CV to help with this?



Figure 1: Lunar Surface⁴



Overview of Project Lifecycle





Overview of Project Lifecycle





Background

Semantic Segmentation: Classifying the class per pixel



Figure 2: Overview of Semantic Segmentation⁵



Data Overview

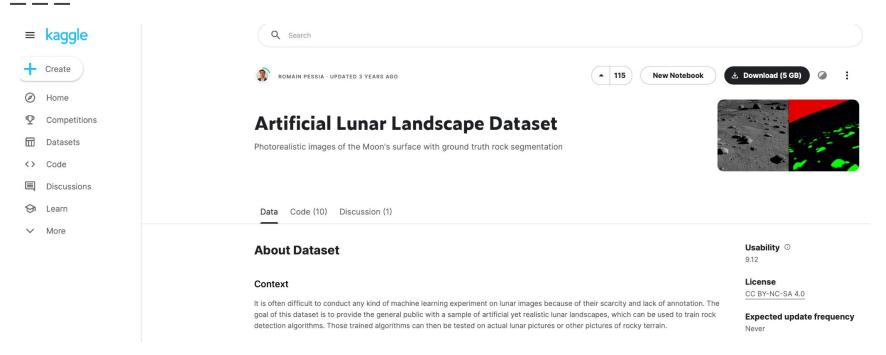
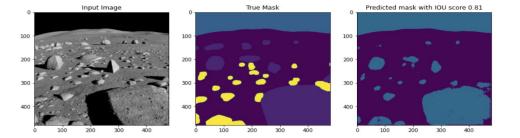


Figure 3: Artificial Lunar Landscape Dataset from Kaggle³

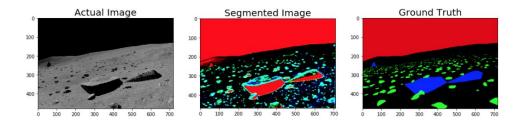


Prior Work on Dataset - Kaggle Notebooks⁷

Gold: Tried VGG16 model



• Silver: Tried VGG16 model





Objectives and Contribution Goals

To build and train our own U-Net based architecture then compare results against a few pretrained networks



Dataset

Rendered Lunar Images:

- 9,766 Images of Rendered Lunar Landscapes
- o 9,766 Ground Truth Masks

Real Lunar Images for Testing:

- 36 Images of Real Lunar Images
- o 36 Ground Truth Masks

Dataset Split	Туре	Percentage of Type
Train	Rendered	49%
Validation	Rendered	21%
Test - Rendered	Rendered	30%
Test - Real	Real	100%

Figure 4: Dataset Split



Rendered Image/Mask Example

Original: render0034.png



Ground Truth Mask: clean0034.png

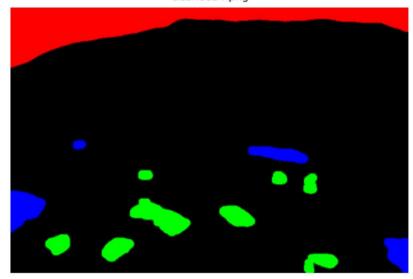


Figure 5: Rendered image and ground truth mask example³



Rendered Image/Mask Example w/ Color Key Labels

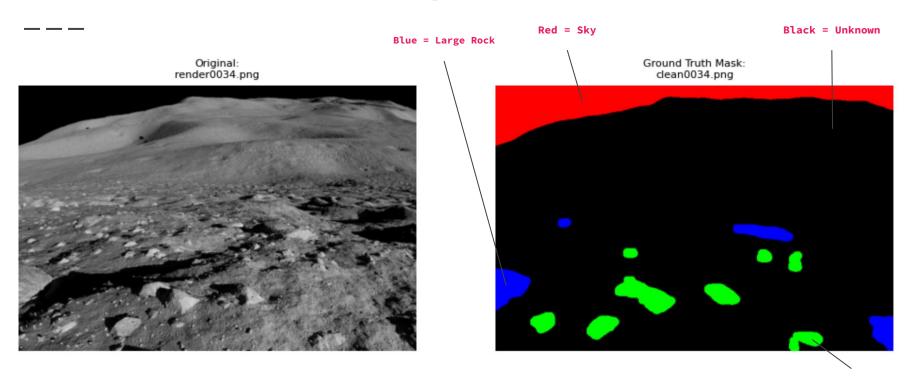


Figure 6: Rendered image and ground truth mask example³ with mask color key labels

Green = Small Rocks



Rendered Image/Mask Example II





Ground Truth Mask: dean3312.png

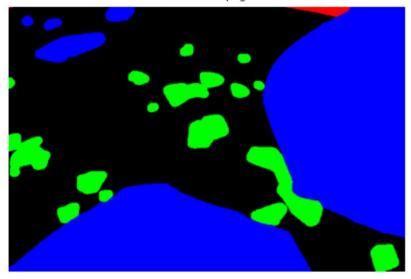
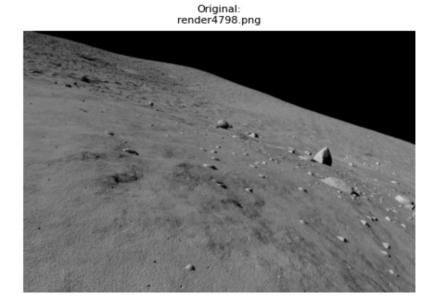


Figure 7: Rendered image and ground truth mask example³



Rendered Image/Mask Example III





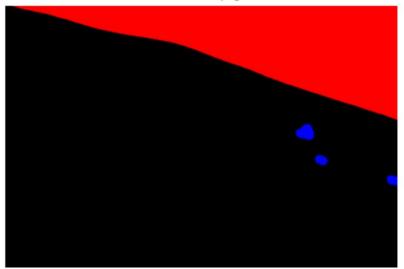
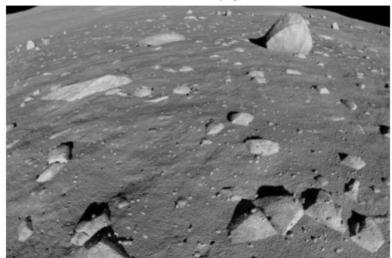


Figure 8: Rendered image and ground truth mask example³



Rendered Image/Mask Example IV

Original: render6182.png



Ground Truth Mask: dean6182.png

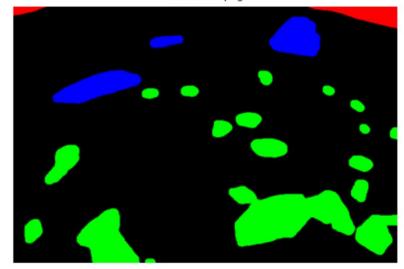


Figure 9: Rendered image and ground truth mask example³



Rendered Image/Mask Example V

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Original: render8455.png



Ground Truth Mask: dean8455.png

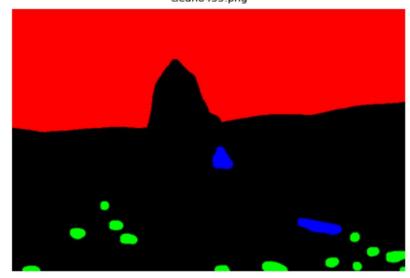


Figure 10: Rendered image and ground truth mask example³



Real Image Example



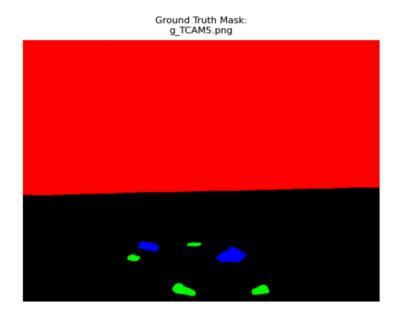


Figure 11: Real lunar image and ground truth mask example³



Real Image Example II



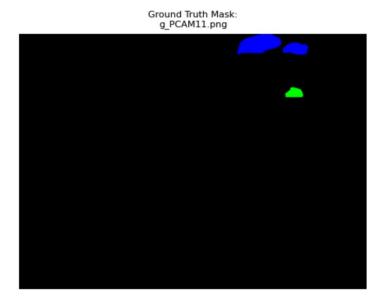
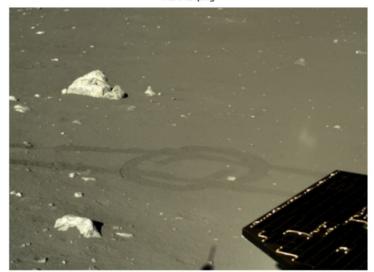


Figure 12: Real lunar image and ground truth mask example³



Real Image Example III





Ground Truth Mask: g_TCAM3.png

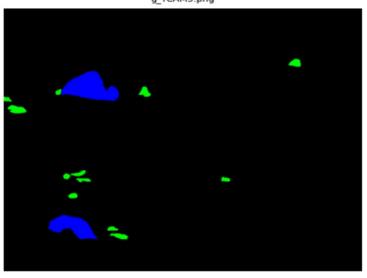


Figure 13: Real lunar image and ground truth mask example³



Overview of Project Lifecycle





EDA

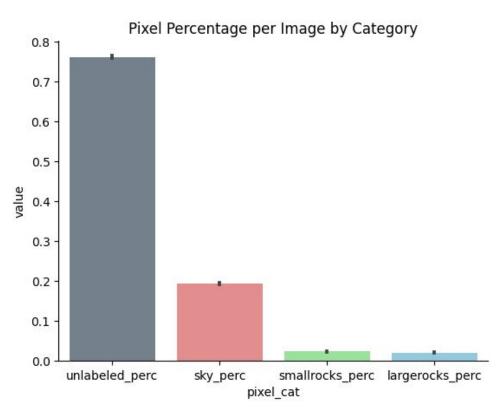


Figure 14: Class Imbalance



EDA

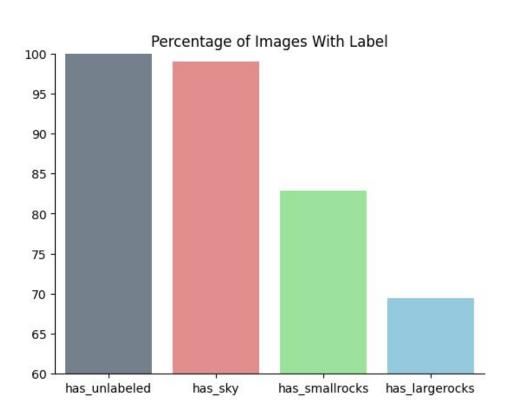


Figure 15: How Many Images Have Which Class Labels



EDA

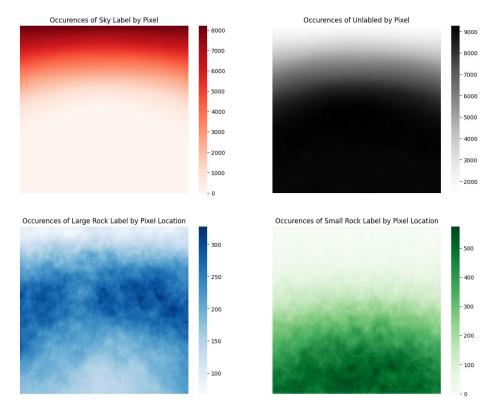


Figure 16: Overall Class Occurence Intensity by Image Location



Overview of Project Lifecycle

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Data Preprocessing

Custom DataLoader

- Loads image and mask
- Resize to 256x256
- Applies data augmentation
- Rescale pixels to between 0-1
- One Hot Encode masks
- Change ordering of channels image dim last
- Convert to torch tensor

Torch DataLoader

Batch data



One Hot Encoding the Ground Truth Mask

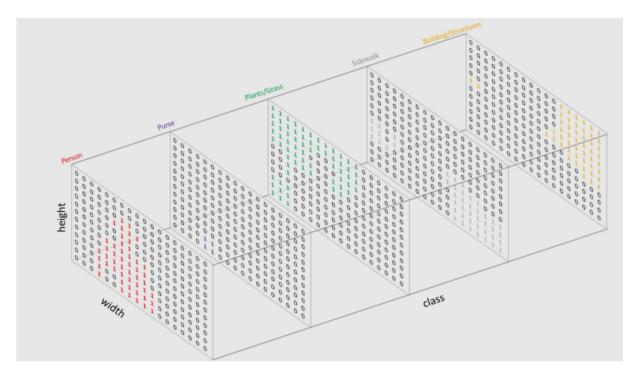


Figure 17: One Hot Encoding the Ground Truth Masks⁵

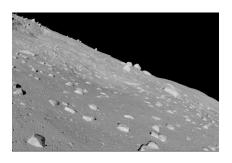


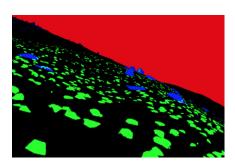
Data Augmentation

- Images & Masks
 - Random Vertical Flip
 - Random Horizontal Flip

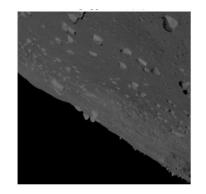
- Images Only
 - Random Color Jitters
 - Brightness
 - Contrast
 - Saturation
 - Hue

Before





After



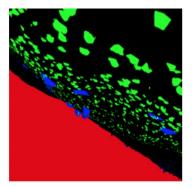


Figure 18: Before and after data augmentation

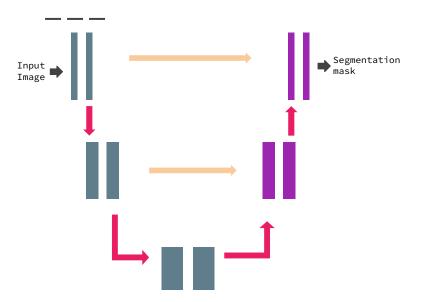


Overview of Project Lifecycle





Model Selection: U-Net



Encoder - Decoder model

• Encoder:

 Down samples the image with convolutional layers and max pooling

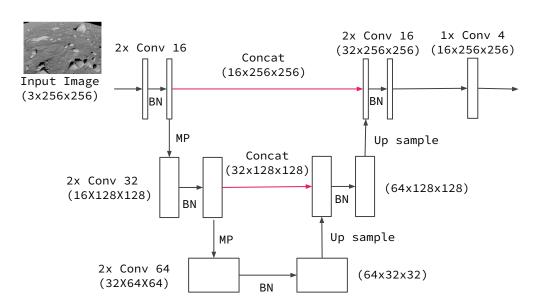
• Decoder:

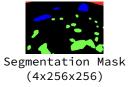
 Up samples the image with transposed convolutional layers

Feature maps from the encoder of the same level are concatenated and passed through the decoder



Our Model





Other Notes:

Block Activation: ReLU

Padding: Same

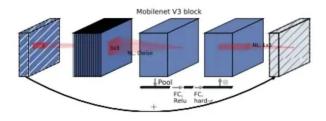
Conv2d Filters: 3x3

Dropouts between all blocks

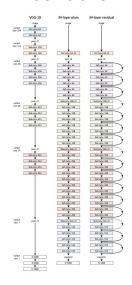


Pre-Trained Models

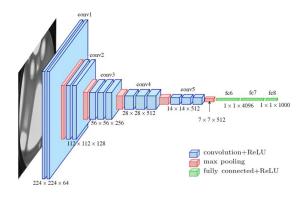
MobileNetv3 Large (Google)



ResNet18



VGG11



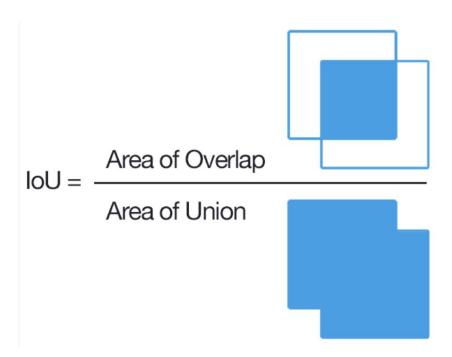
Parameters 5.4 M 11 M 18 M

Metrics

Jaccard's Index (IOU):

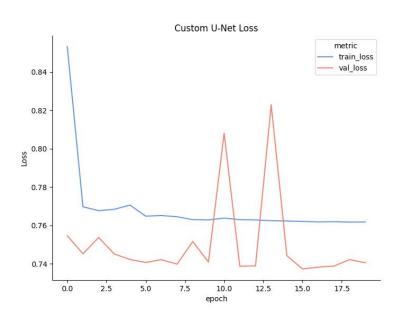
 Measures how much overlap exists between the predicted mask and the true mask

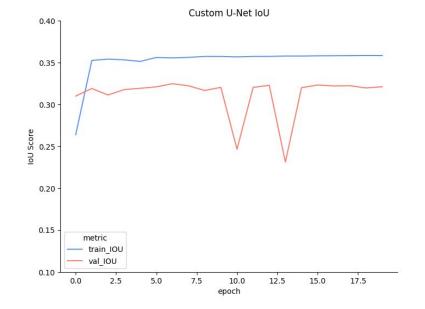
$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$





Model Training: Custom U-Net



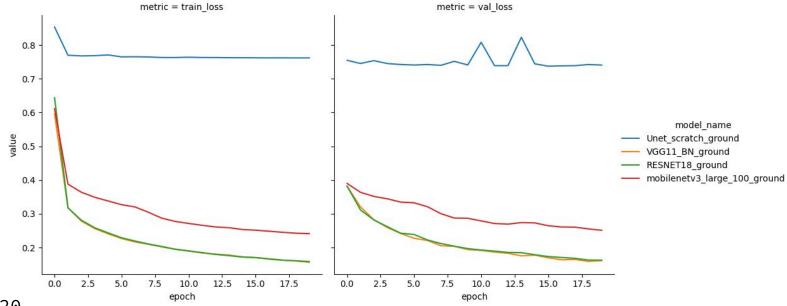


Epochs - 20
Optimizer - Adam
Loss - Cross Entropy Loss



Model Training: Pre-trained U-Nets

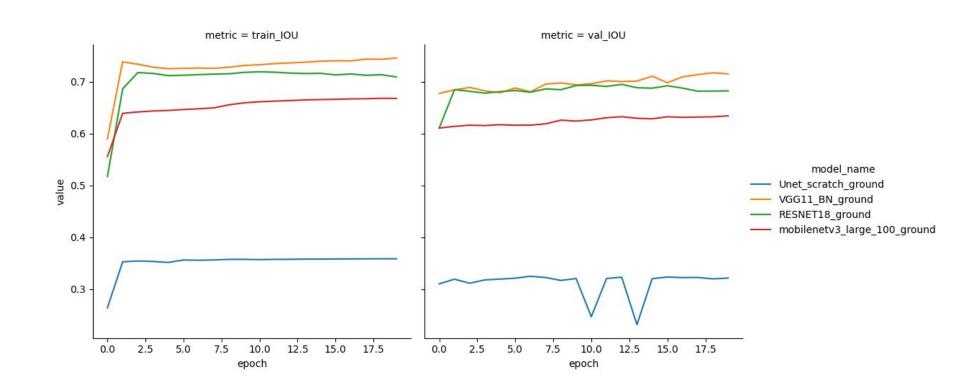




```
Epochs - 20
Optimizer - SGD
Loss - Cross Entropy Loss
```

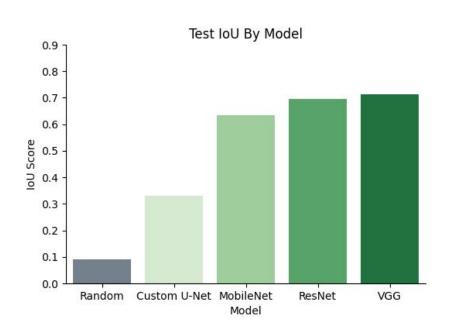


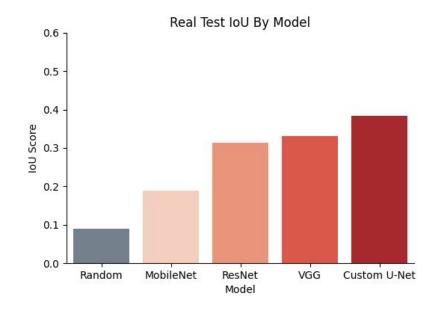
Model Training: Pre-trained U-Nets





Model Results: Model Testing





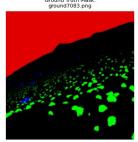


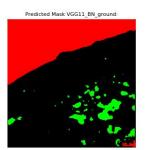
Model Results: Example Rendered Segmentations

VGG11

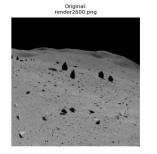
Original: render7083.png

Ground Truth Mask:





Custom Model









Model Results: Example Real Image Segmentation

Original: TCAM15.png

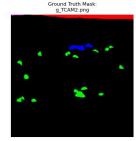
Custom Model

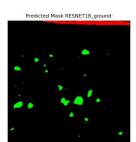
Ground Truth Mask:
g_TCAM15.png Predicted I

Predicted Mask Unet_scratch_ground:



ResNet





IOU: 0.48 **IOU:** 0.46



Model Results: Example Real Image Segmentation

Original: TCAM2.png

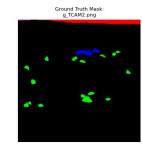
Custom Model

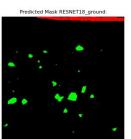
Ground Truth Mask:

g TCAM2.png



ResNet





IOU: 0.44 **IOU:** 0.46



Overview of Project Lifecycle

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Interpreting Results

- The VGG11 Model was the strongest model we trained
 This is likely due to being the largest model
- Our custom model underfit the dataset
- None of the models performed well on the real lunar images



Final Words and Areas of Improvement

- We succeeded in comparing multiple different pre-trained U-Nets
 - Although the conclusion we came to was consistent with previous attempts to solve this problem
- In the future:
 - Run full hyperparameter grid-search
 - Attempt adding attention to the models
 - Increase the complexity of the scratch model to attempt and compete with the pre-trained models

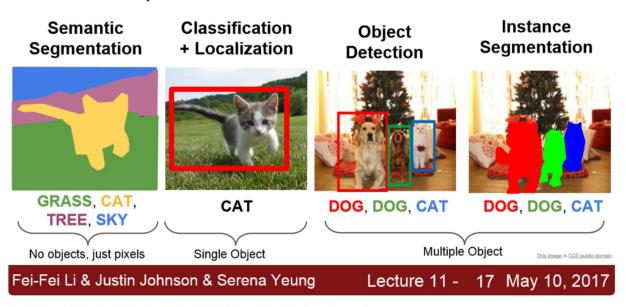
References

- 1. <u>Jonathan Long et. al (2014) Fully Convolutional Networks for Semantic Segmentation</u>
- 2. Ronneberger et. al (2015) UNet: Convolutional Networks for Biomedical Image Segmentation
- 3. Artificial Lunar Landscape Dataset on Kaggle
- 4. <u>Lunar Surface Image thespaceacademy.org</u>
- 5. <u>An Overview of Semantic Segmentation</u>
- 6. <u>Stanford CS231: Detection and Segmentation</u>
- 7. <u>Kaggle Artificial Lunar Landscape Dataset</u>
- 8. <u>Kaggle Artificial Lunar Landscape Dataset Silver Notebook</u>
- 9. <u>Jaccard Index</u>
- 10. Understanding and Visualizing ResNets
- 11. Architecture and Implementation of VGG16
- 12. MobileNet v3
- 13. Metrics to Evaluate Semantic Segmentation
- 14. <u>Cross Entropy Loss</u>



Background

Other Computer Vision Tasks



Source http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture11.pdf

Figure X: Overview of CV Tasks⁶



Environment Setup/Data Download



(GPU available)

Model Results: ...

- Not sure if we wanna show class breakdowns for a couple like this with the predictions, might be better for the report.
- depending on what plots i make for the results I might put on of these in there, they're pretty so they'll for sure be in the report lol

Something like this->

