Habitat-Net

Habitat interpretation using deep neural nets

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Motivation

- Segmentations of habitat images

Forestry and Ecology

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  - Quantitative Habitat interpretation
  - Location for camera traps
  - Assess biodiversity
  - Assess species distribution

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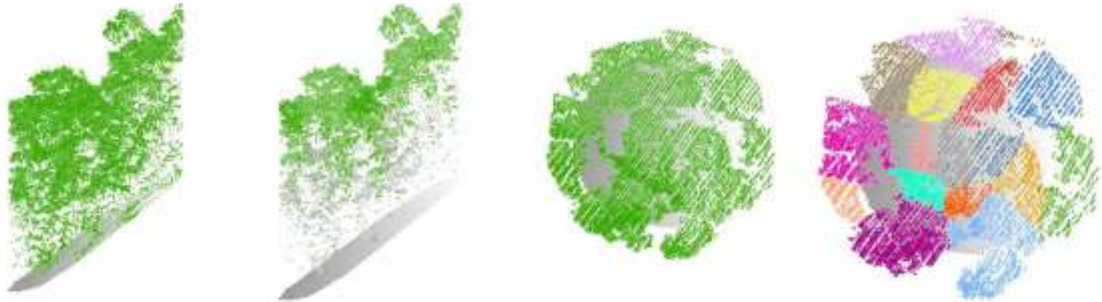
No existing deep learning-segmentation model in ecology

Related work

- Mostly LiDAR based
  - Super-expensive



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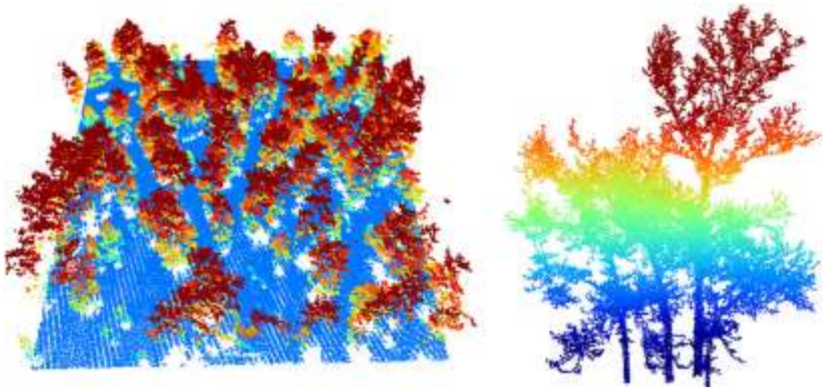

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- Mostly LiDAR based
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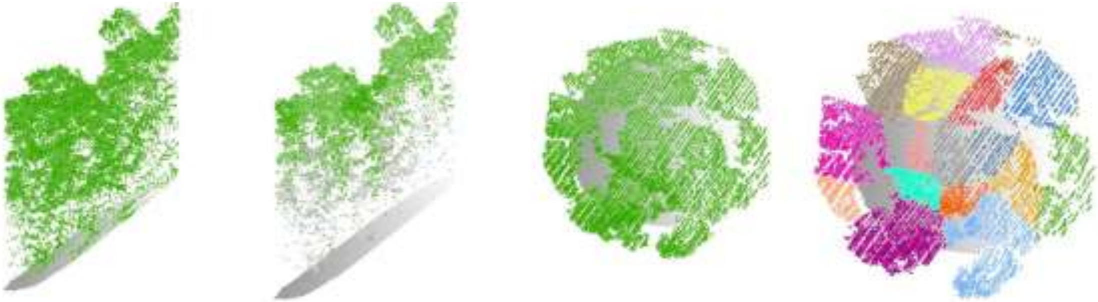
- LiDAR vs photographs
  - Photo for most people
  - Cheap and Practical



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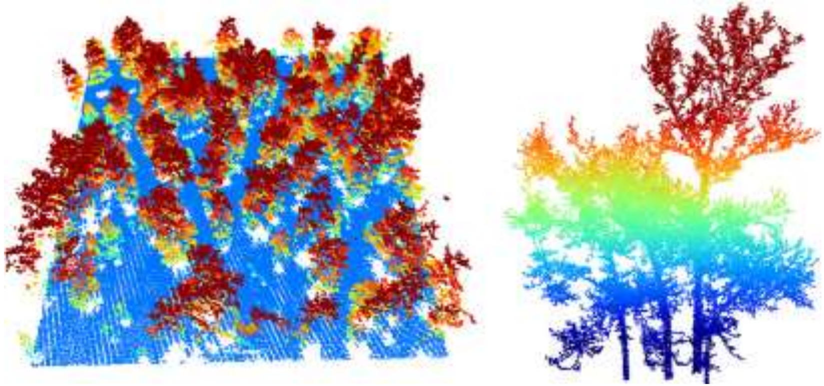

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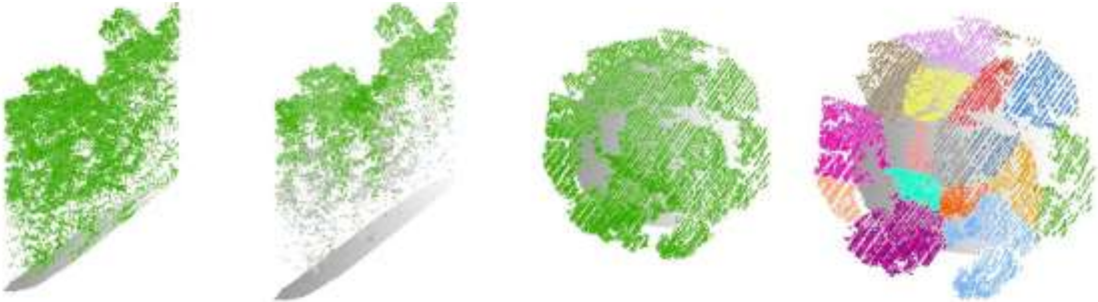
- **No segmentation** method
  - habitat photographs



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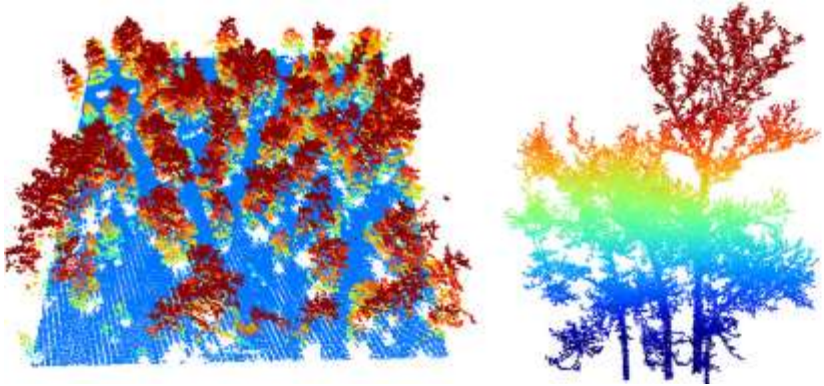

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Convolutional Neural Network (CNN) vs U-Net

- CNN
  - Image in, Recognition out

CNN vs U-Net

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  - Image in, Recognition out
  - Ecology context
    - Camera Trap image in
    - Species Id out

Norouzzadeh, PNAS 2018

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Norouzzadeh, PNAS 2018

- U-Net
  - Image in, Segmentation out
  - Grayscale bio-medical images

Ronneberger, MICCAI 2015

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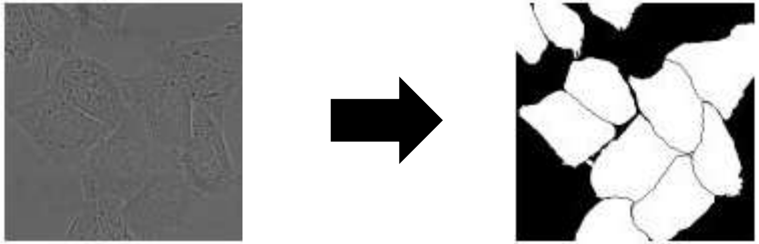
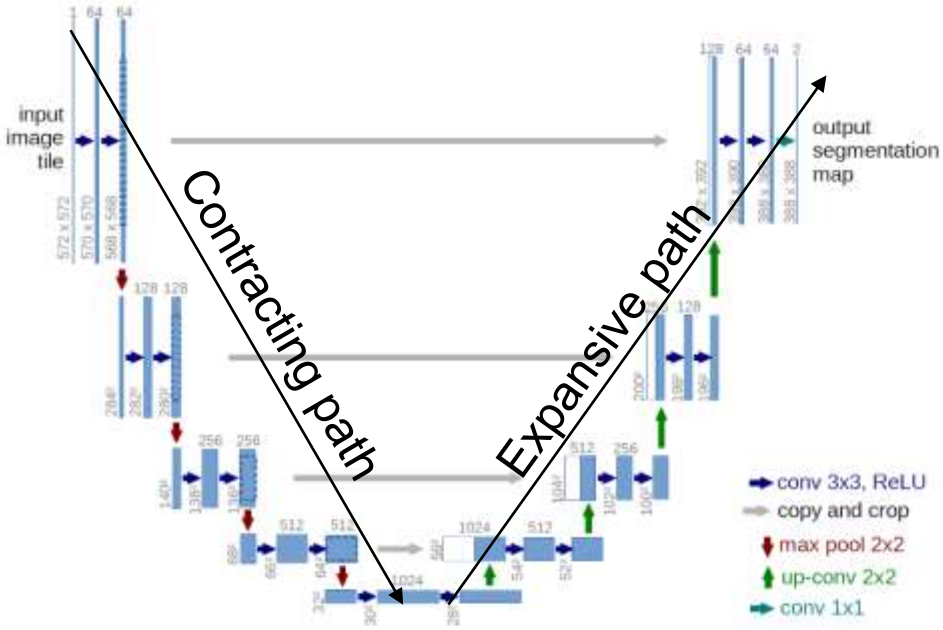


Ronneberger, MICCAI 2015

Overview: U-Net

- Encoder-decoder CNN
  - Skip Connections



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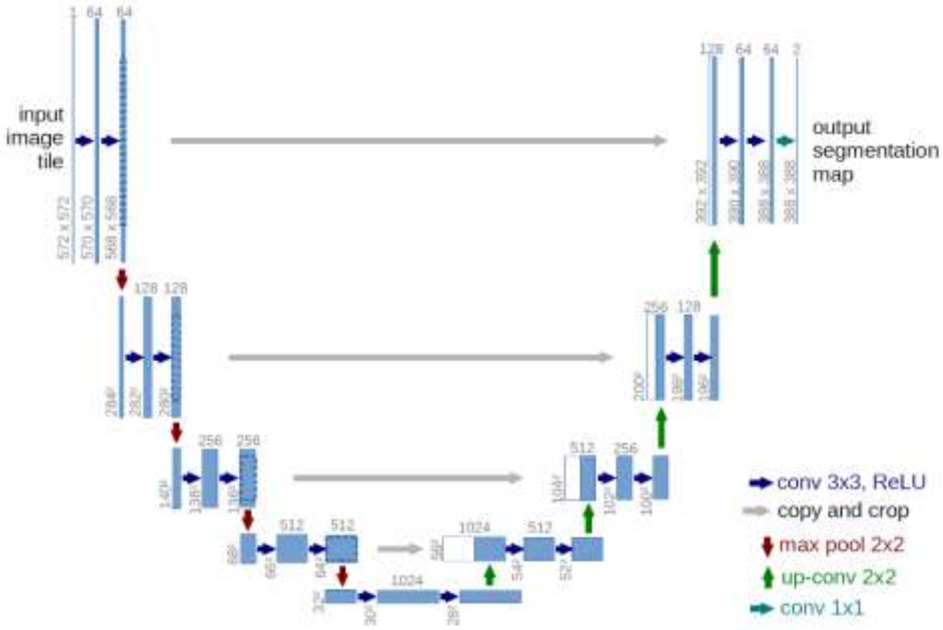

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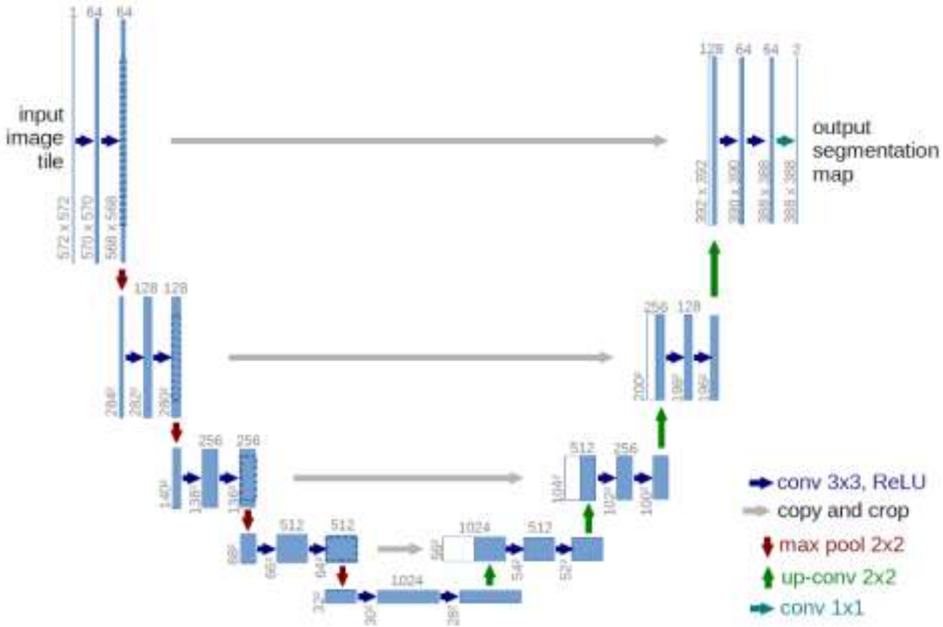
- Works well
  - Very few annotations



Overview: U-Net

- Encoder-decoder CNN
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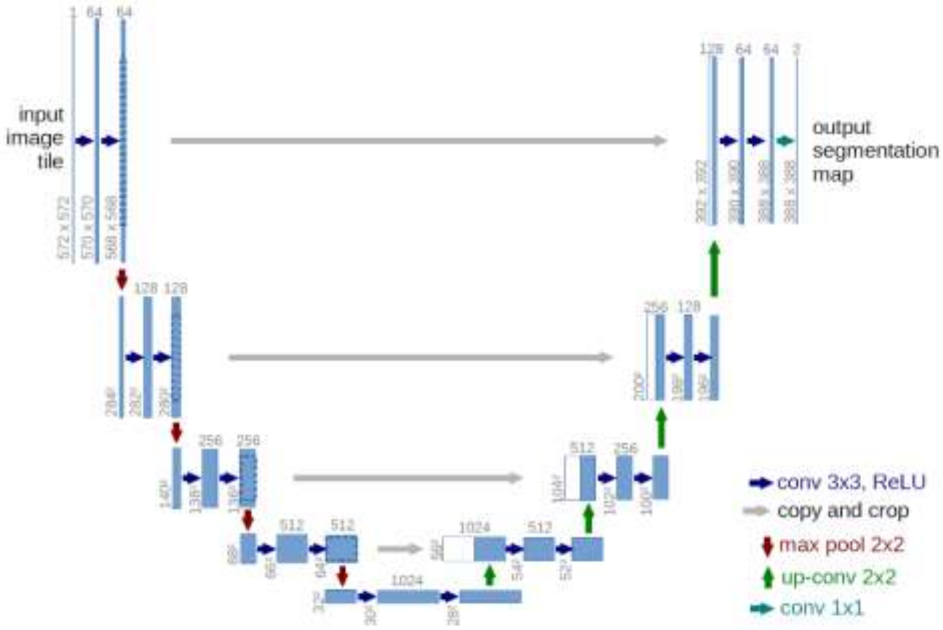
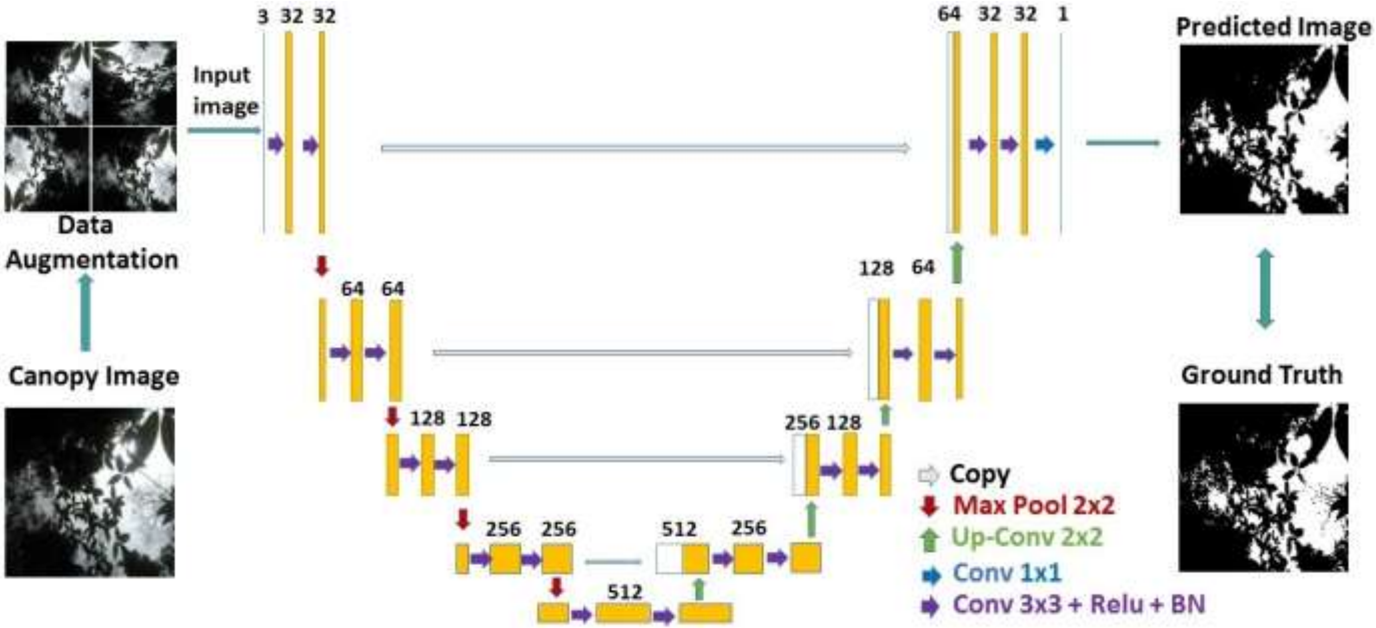
  - Image in, Segmentation out
- Works well
  - Very few annotations
  - Grayscale images as input



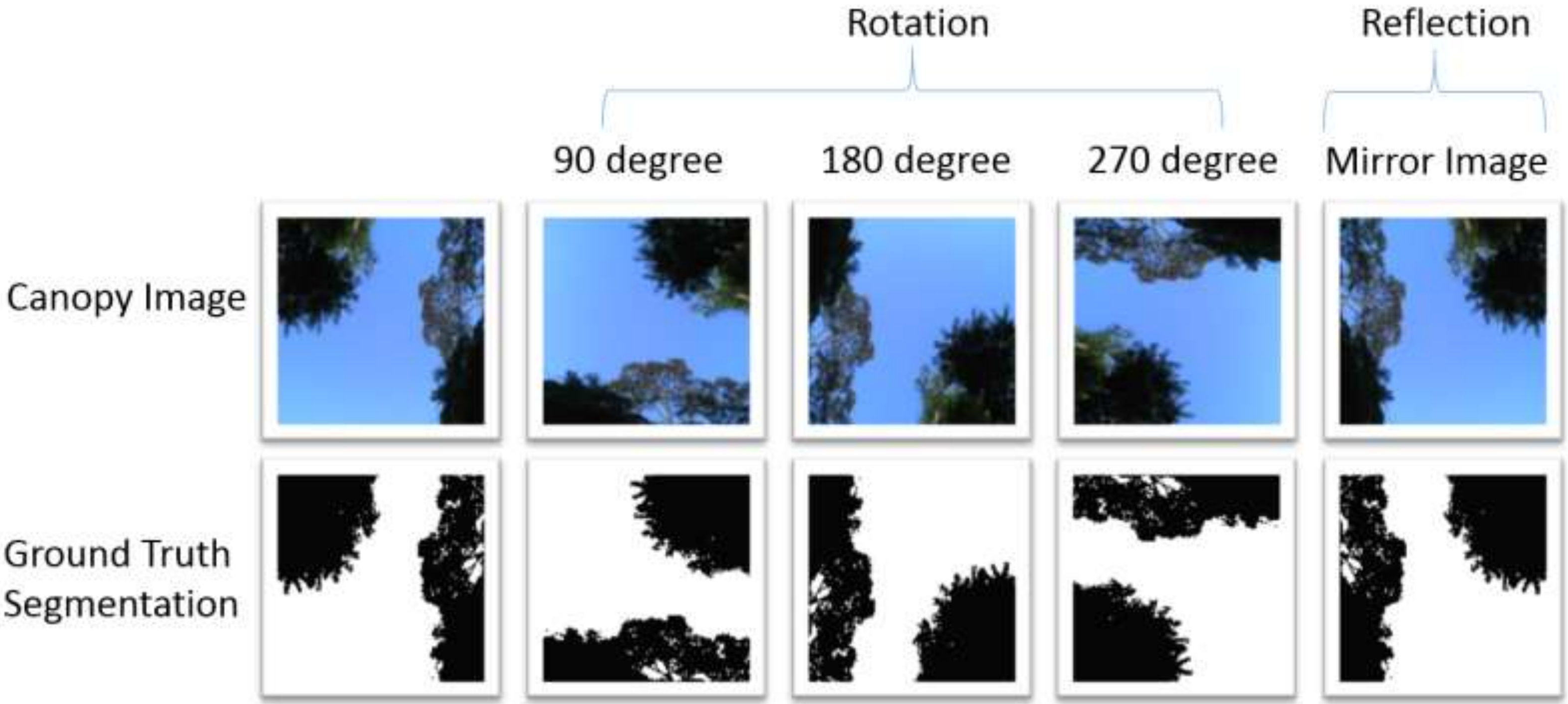
Habitat-Net

Total 33 convolutions

~4 million parameters

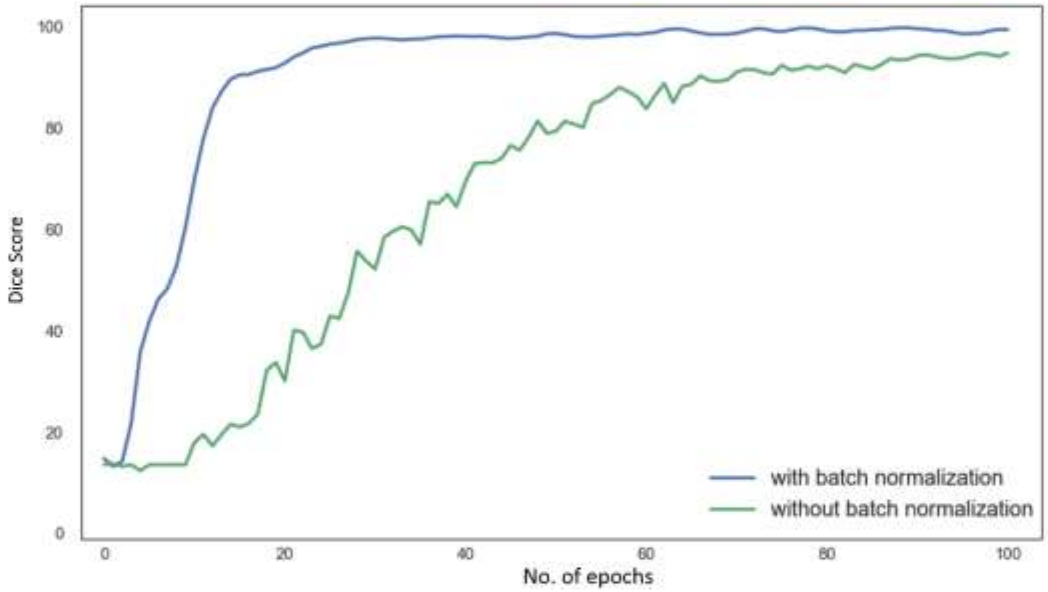


Habitat-Net: Data Augmentation



Habitat-Net: Batch Normalization

- Same accuracy with fewer training steps.



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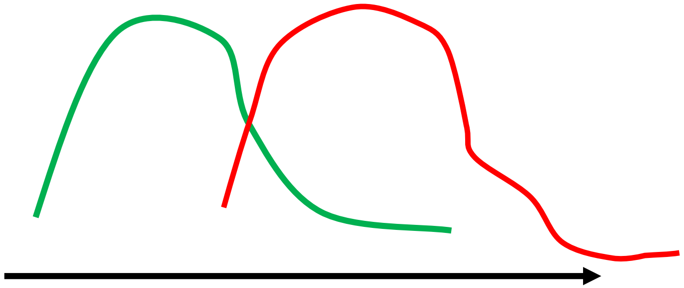
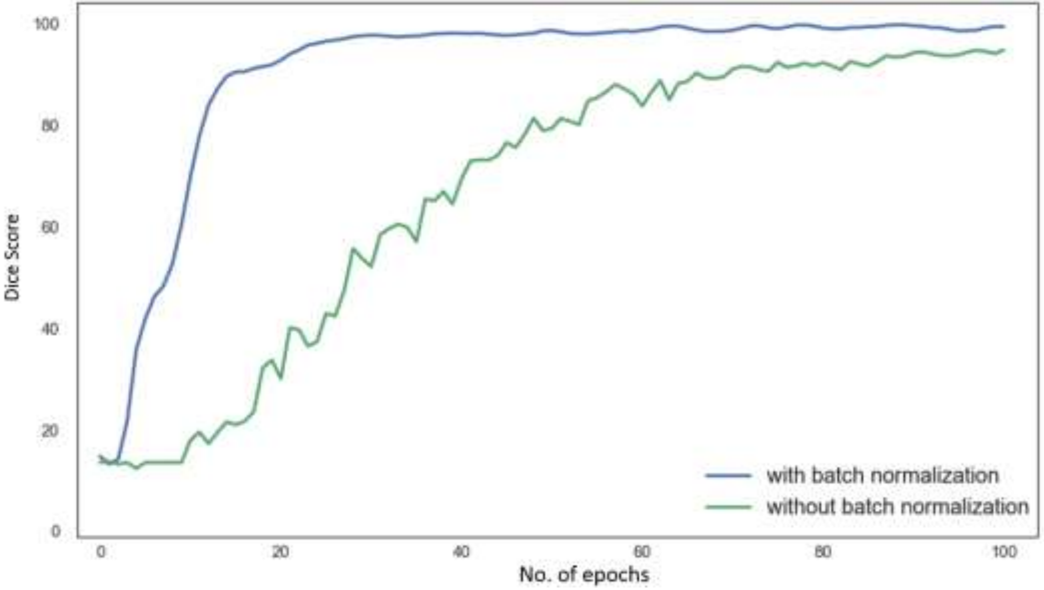
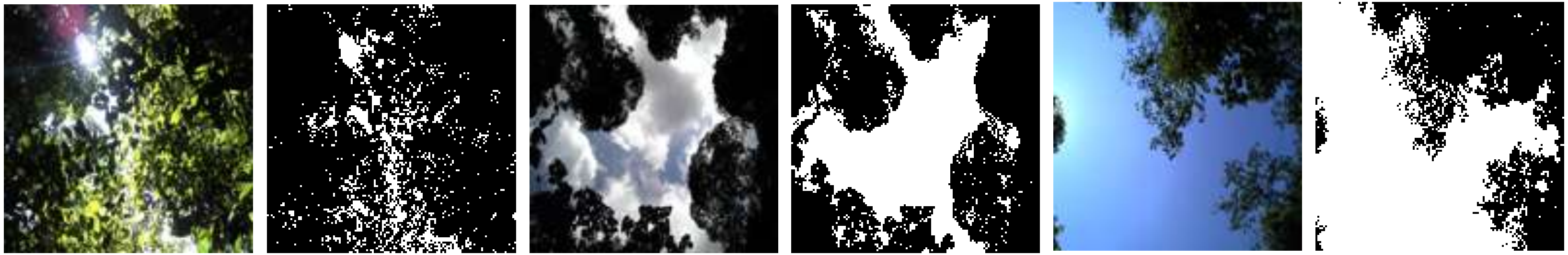


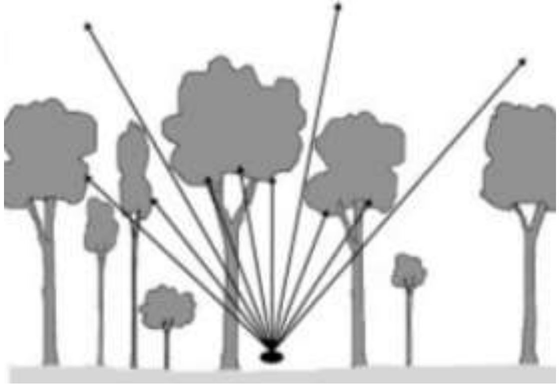


- Acts as a regularizer.

Data Description

- Canopy closure: The upper layer formed by mature tree crowns.





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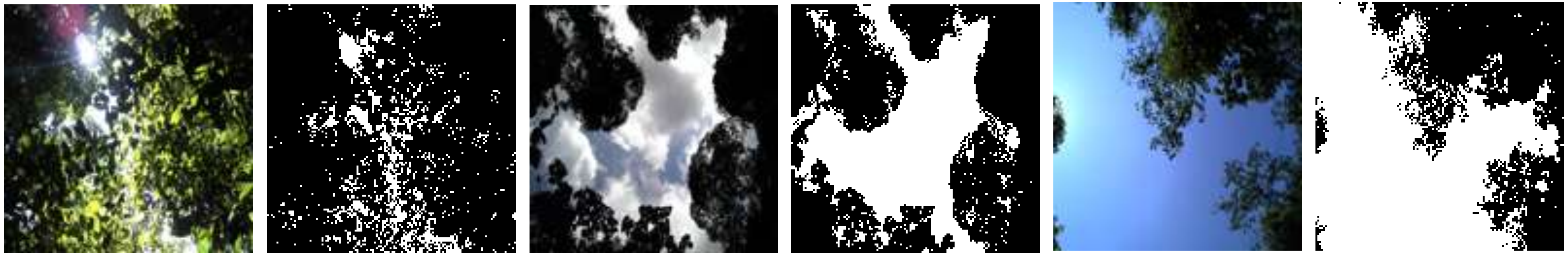
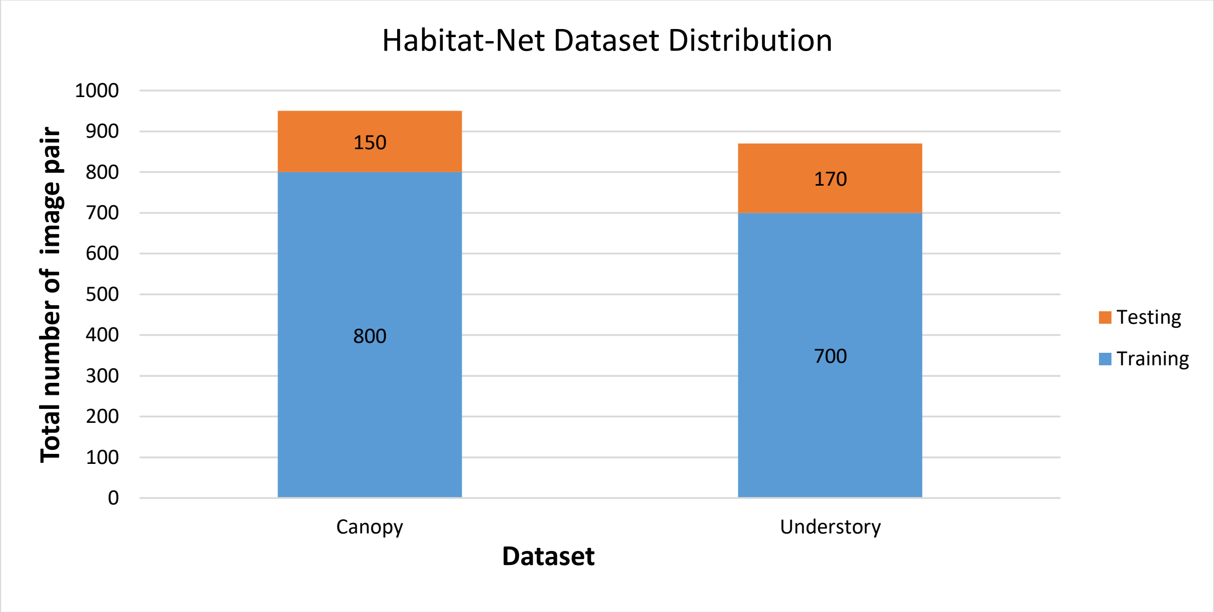


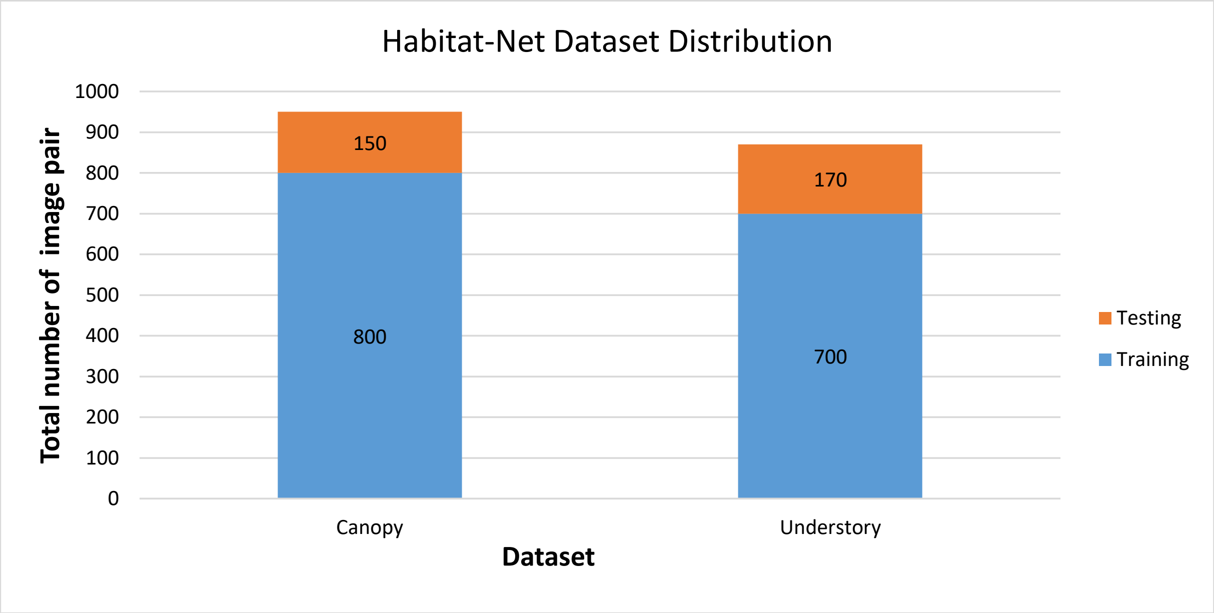
- Understory: Plant life growing beneath the forest canopy above the forest floor.

Data Description



- Canopy:
  - Total: 950
  - Resolution: 128×128

Data Description



- Canopy:
  - Total: 950
  - Resolution: 128×128
- Understory:
  - Total: 870
  - Resolution: 256×160

Data Description

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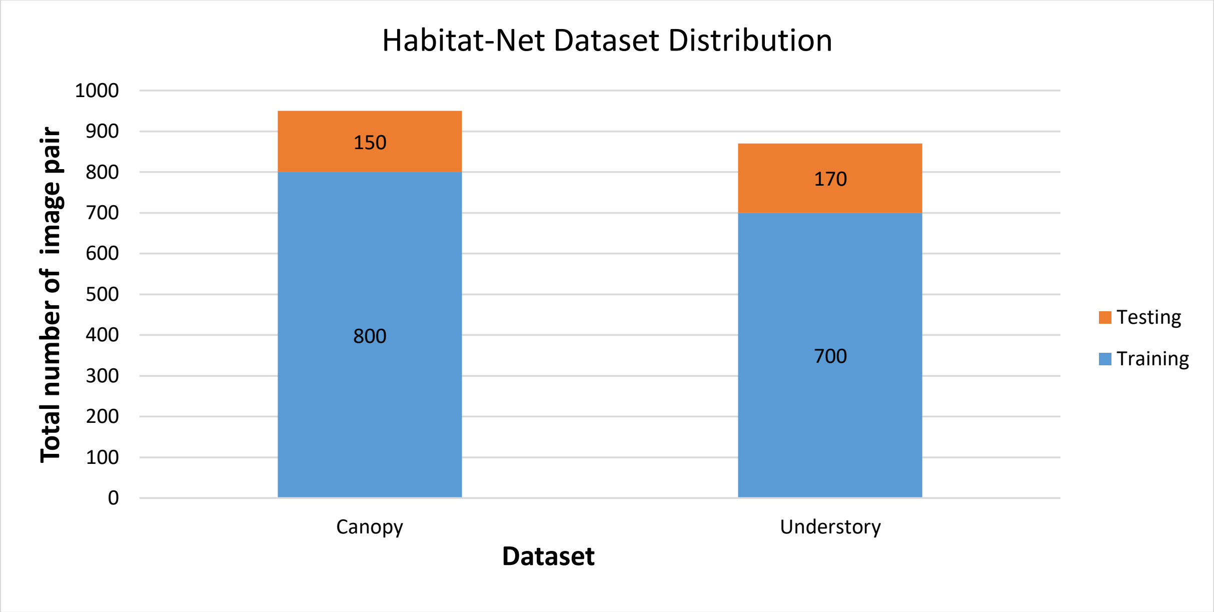

- Canopy:
  - Total: 950
  - Resolution: 128×128
- Understory:
  - Total: 870
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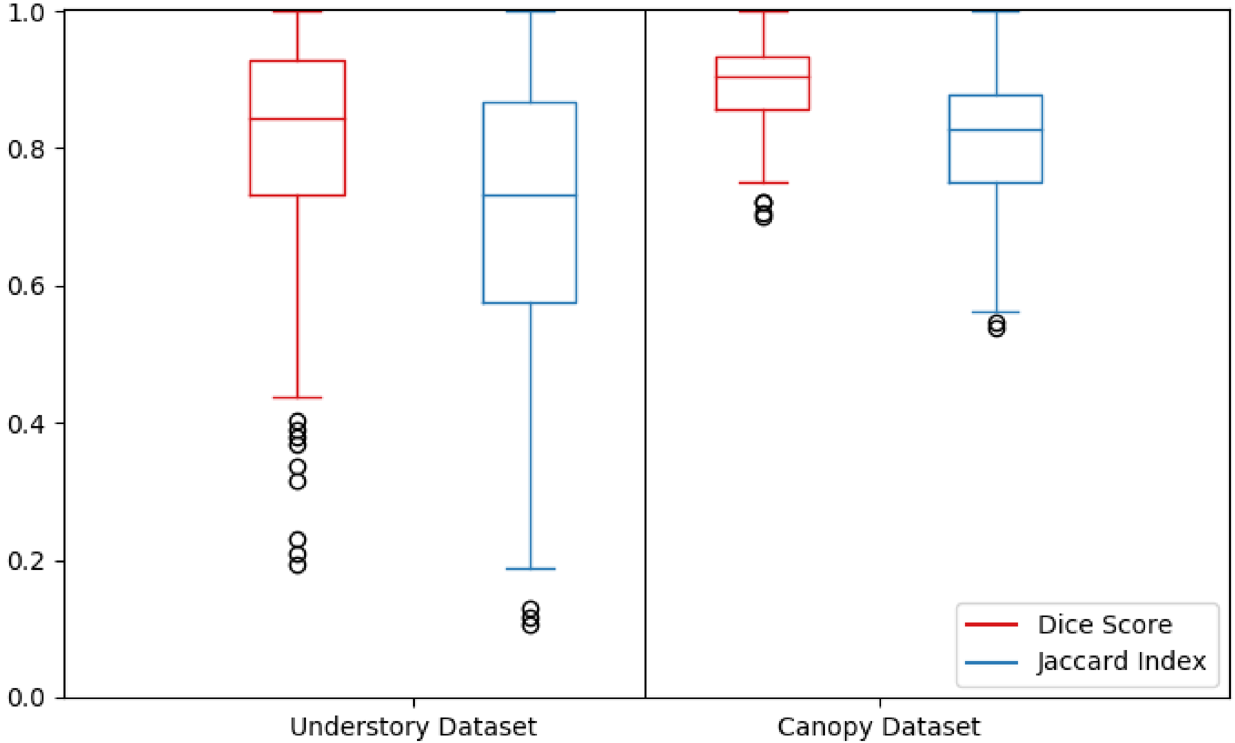
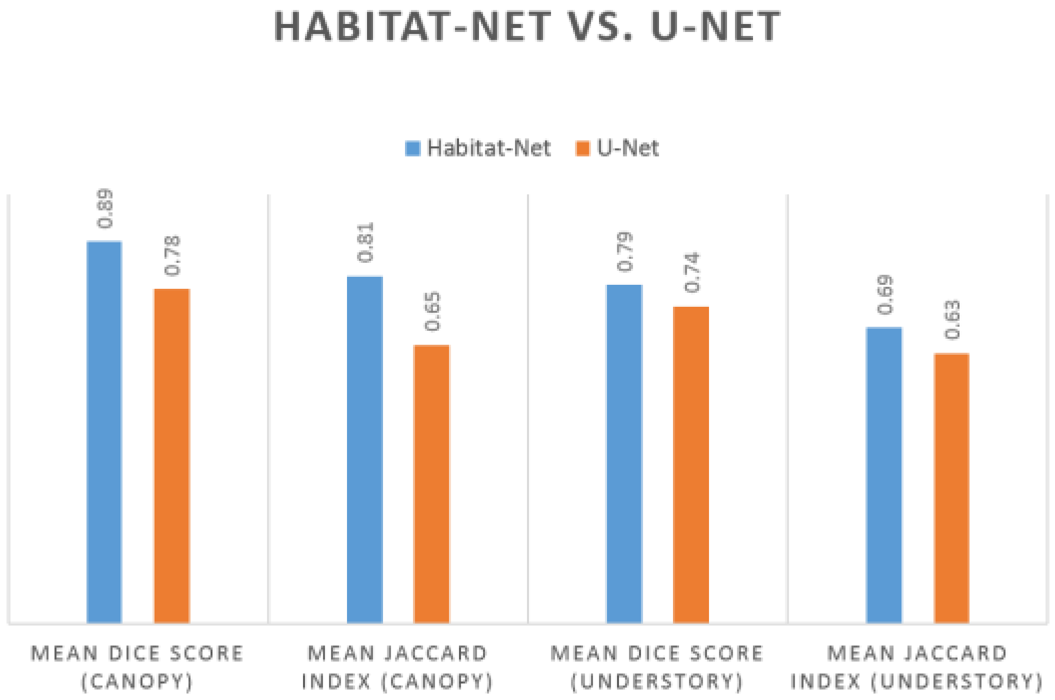
Validation set: 15% of training set

Results

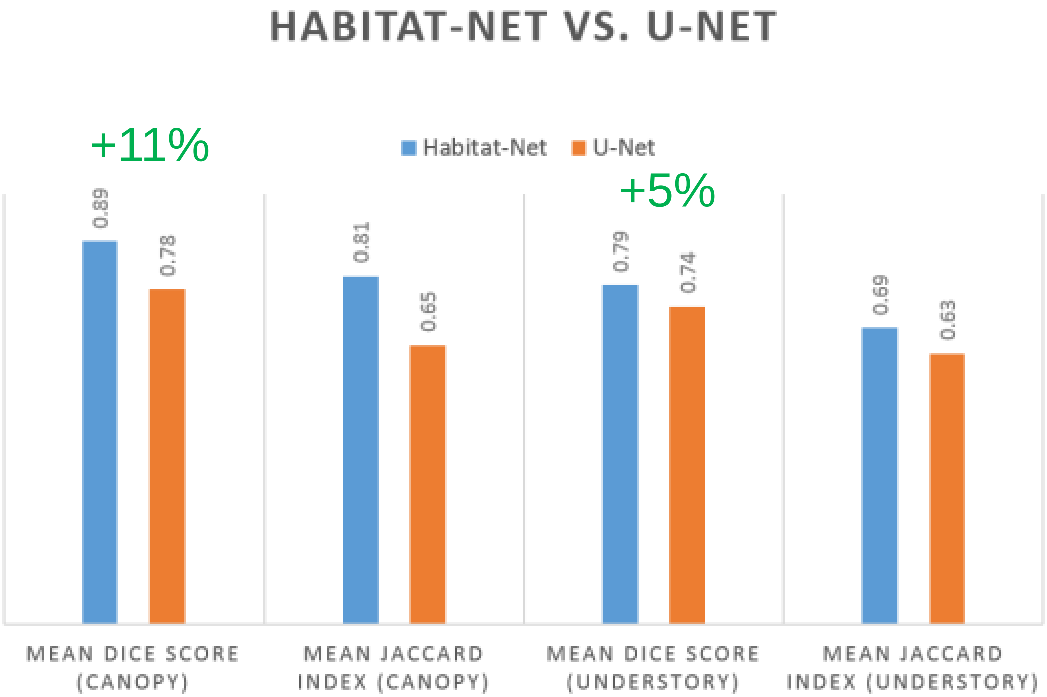

1.0
0.8
0.6
0.4
0.2
0.0
Understory Dataset
Canopy Dataset
Dice Score
Jaccard Index

Quantitative Comparison



Using same network depth and hyper parameters

Quantitative Comparison



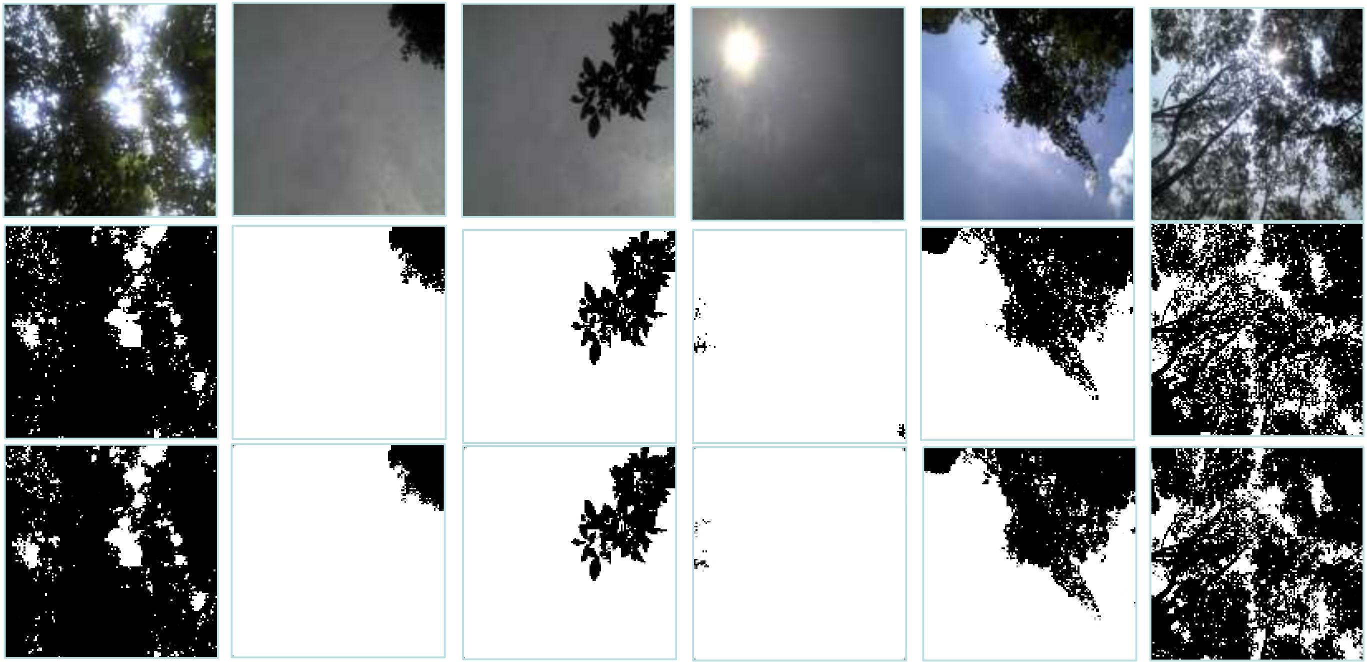
Using same network depth and hyper parameters

Qualitative analysis: Canopy

Actual Image

Ground Truth

Prediction Image

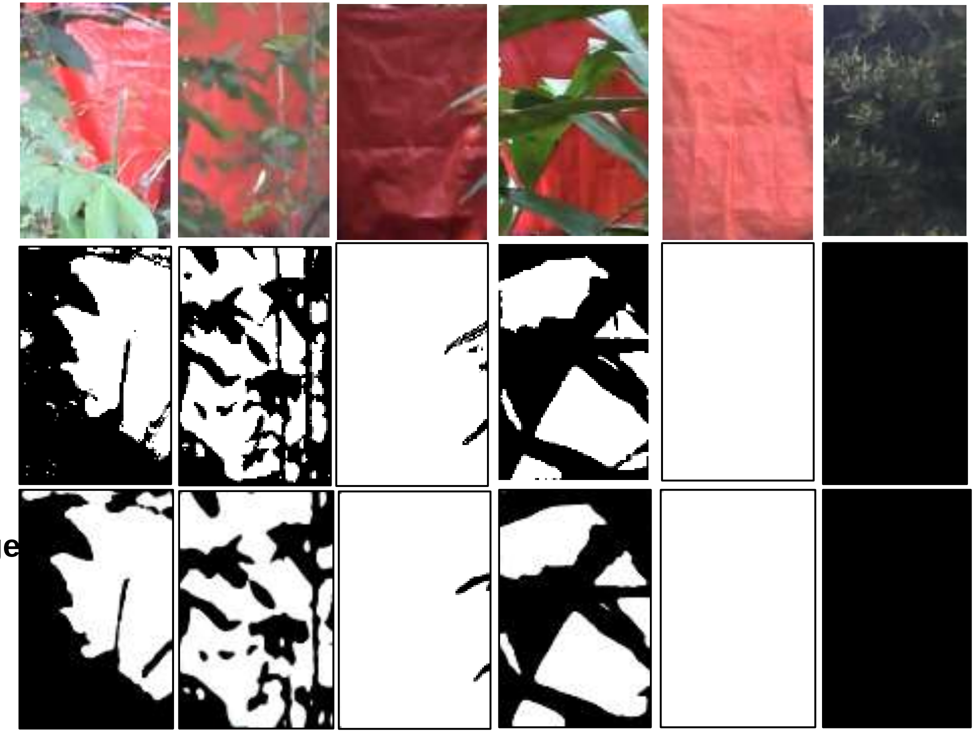


Qualitative analysis: Understory

Actual Image

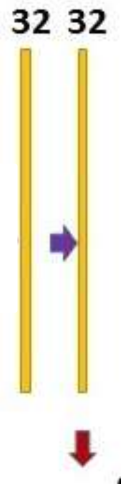
Ground Truth

Prediction Image



Habitat-Net code

```
conv1 = Conv2D(32, (3, 3), activation='relu', padding='same')(conv1)
conv1 = BatchNormalization(axis=-1, momentum=0.99)(conv1)
conv1 = Conv2D(32, (3, 3), activation='relu', padding='same')(conv1)
conv1 = BatchNormalization(axis=-1, momentum=0.99)(conv1)
pool1 = MaxPooling2D(pool_size=(2, 2))(conv1)
```



Implementation: Keras with Tensorflow backend
Trained Networks available
Beta Version: https://github.com/Kanvas89/Habitat-Net

Summary

- First of it’s kind
  - Deep learning to segment ecological images for habitation interpretation

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- Habitat-Net: ~15 milli-sec/ image
  - Humans: ~45 sec/image
- Accurate: Quantitatively and Qualitatively
- Practical
  - Code and trained network available
  - Sample data will be available soon

Conclusion

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- Innovative **Deep-Learning toolkit for Ecology**
  - Need of the hour

Thank You ☺ Questions?

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