

# Estimating Forest Ground Vegetation Cover From Nadir Photographs Using Deep Convolutional Neural Networks

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# Motivation

Forest fires, such as those on the US west coast, are an important factor in climate change and their propagation can be modeled by analyzing the ground vegetation cover.



Image credits: BBC News([Source](#))

# Wildfire modeling (Current practice: manual classification)

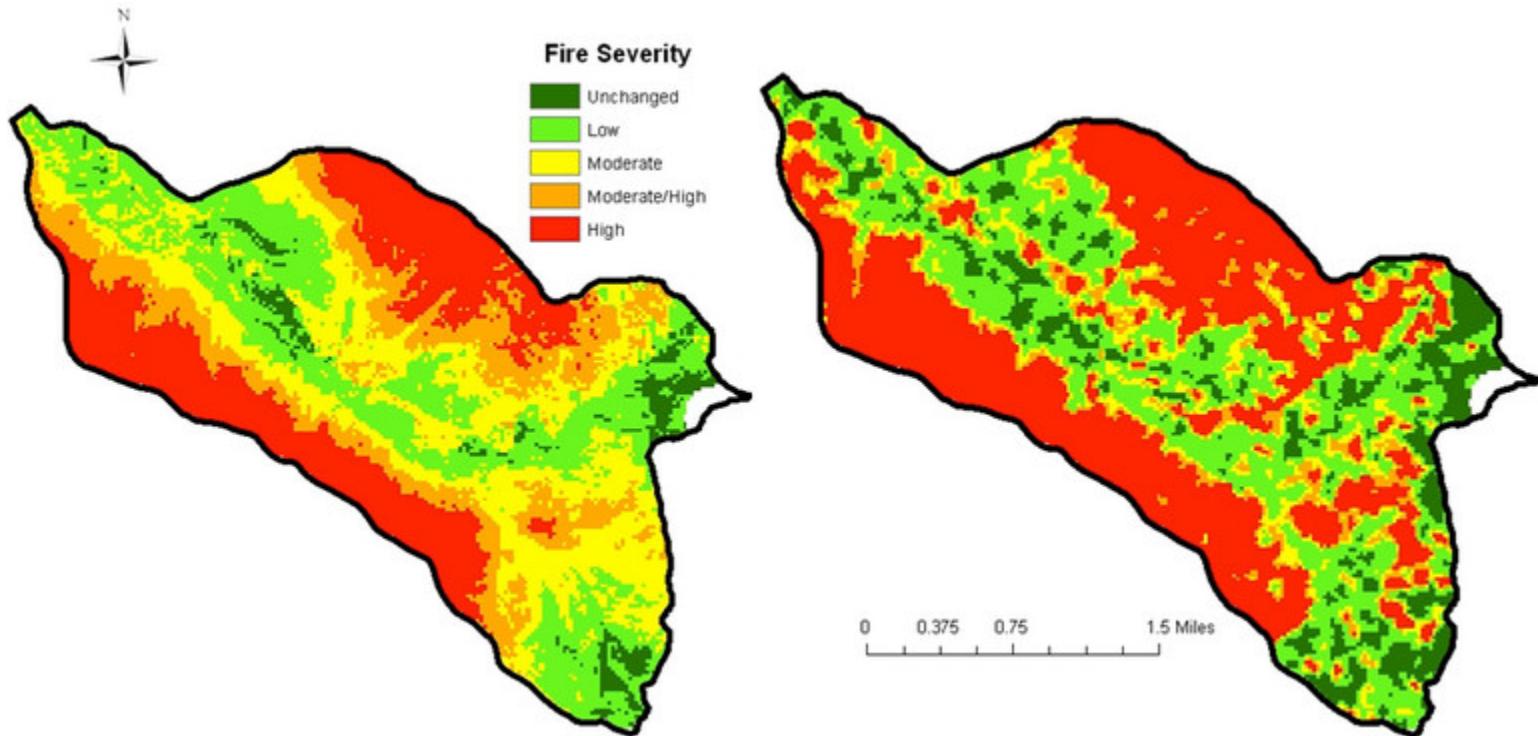
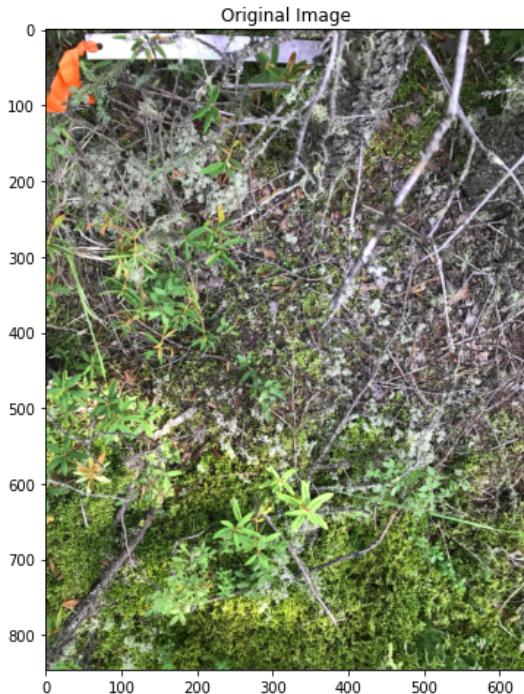


Image Credits: Penn State News([Source](#))

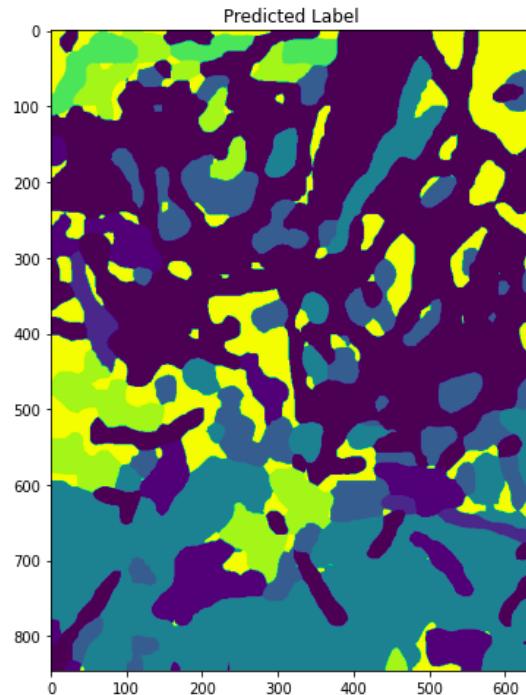
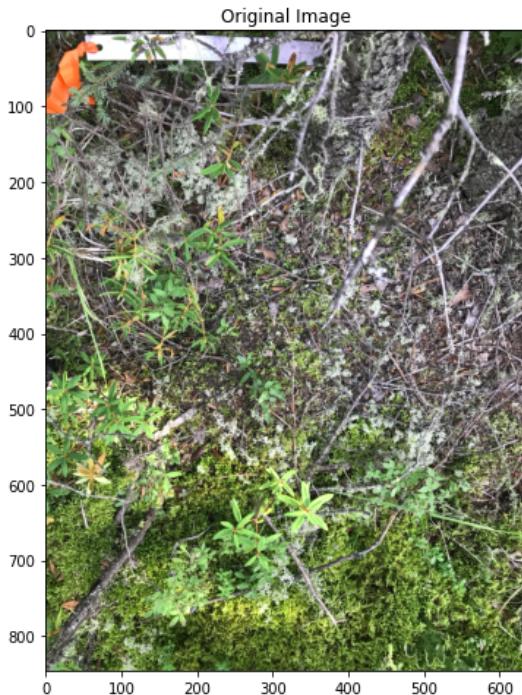
# Problem Statement

- In this work, we propose automating the process of vegetation cover classification from raw images taken either by field personnel or drones.

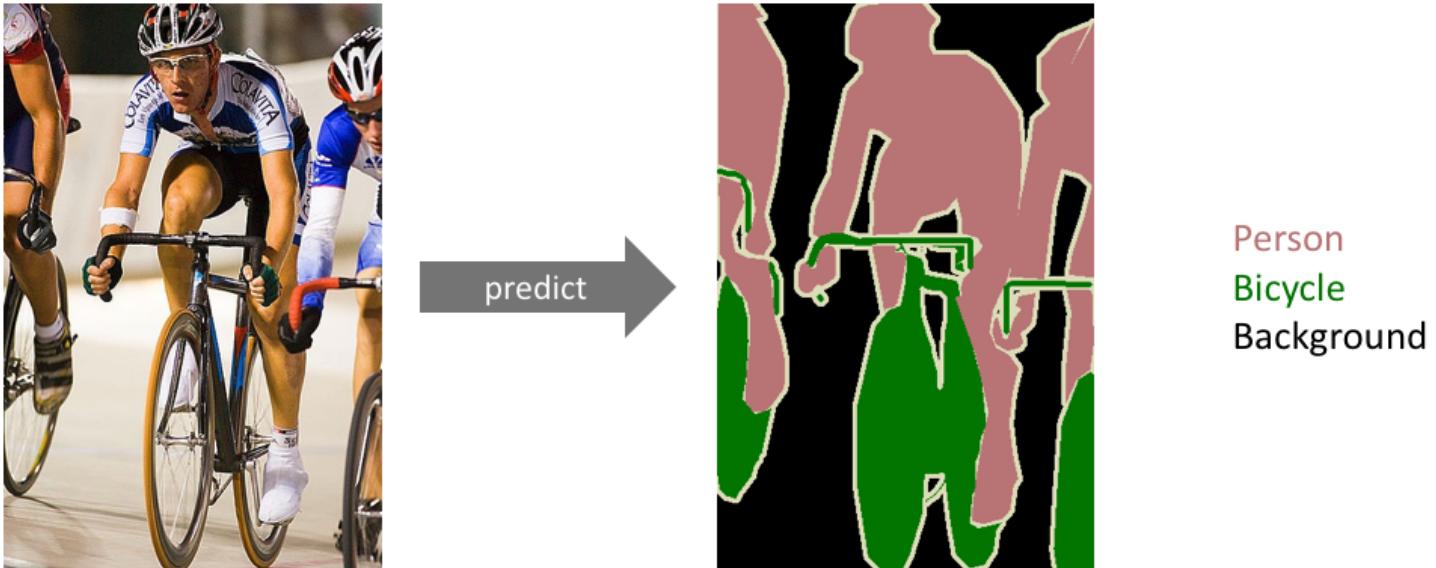


# Problem Statement

- In this work, we propose automating the process of vegetation cover classification from raw images taken either by field personnel or drones.



- The task of vegetation cover classification is analogous to the semantic segmentation problem in the field of computer vision.



# Our Method

- We use a deep convolutional neural network (base model: DeepLab v3) to tackle this semantic segmentation task.
- Deep learning is sample-inefficient.
- This is a big problem for us since there are no publicly available large-scale datasets of ground vegetation cover segmentation.

# We create our dataset :

1. Ground crews collected images from 28 field sample plots. Total number of images available to us was 330.
2. A human expert labelled these images using the tool [PixelAnnotationTool](#).



Image credits: wildefireanalytics.org([Source](#))

# We applied *Transfer Learning*

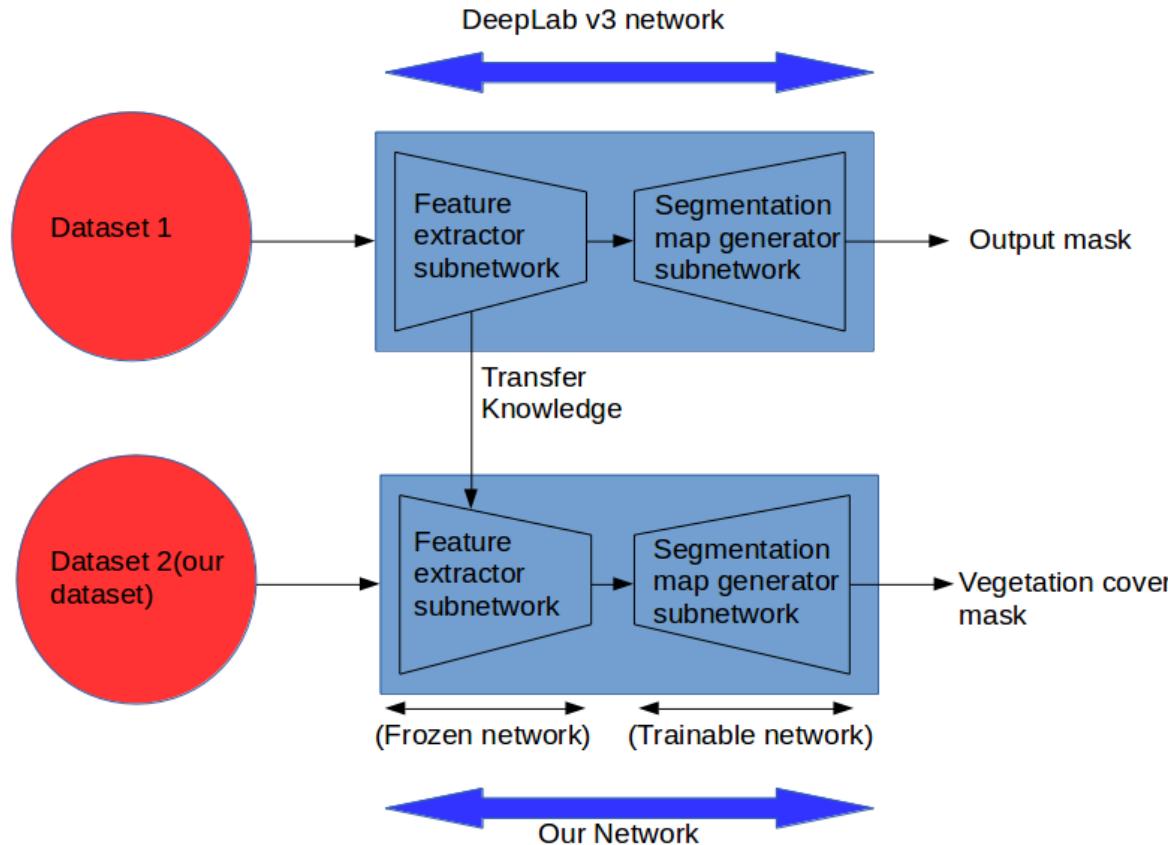


Figure: Transfer Learning framework

# To increase performance we applied data augmentation

We used the following data augmentation techniques:

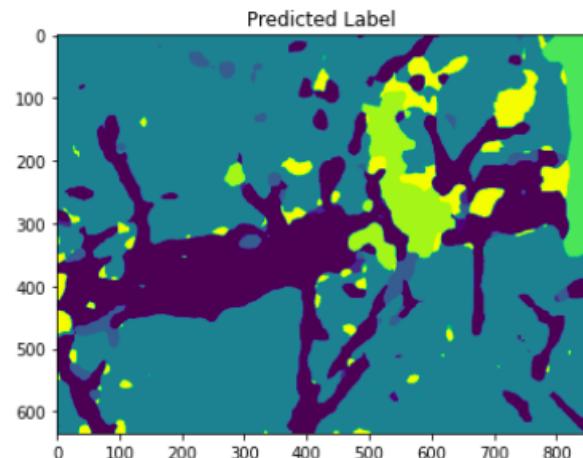
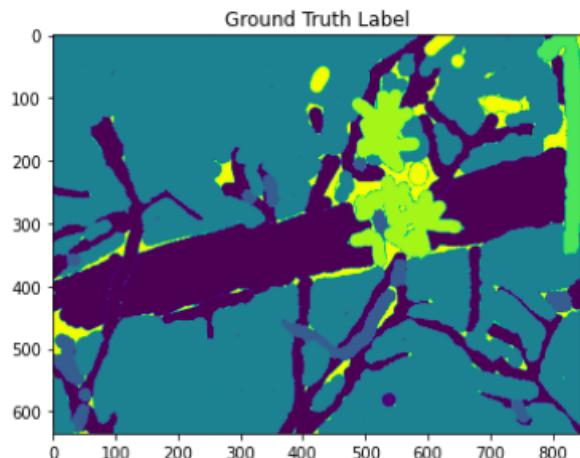
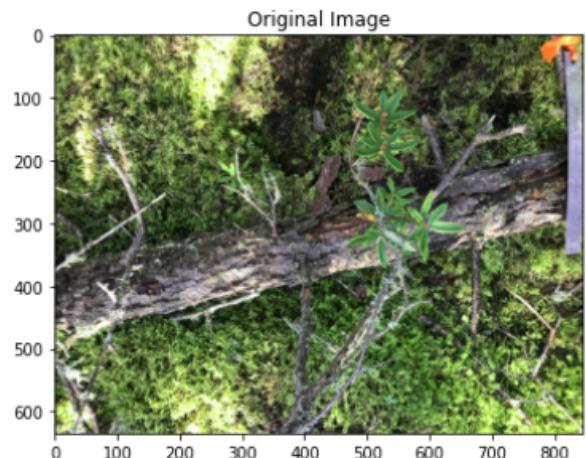
1. Horizontal flip
2. Gaussian noise addition
3. Contrast reduction

(Note: The **contrast reduction strategy** was specifically motivated by our application, namely given that we expect the images to contain shadows occluding the vegetation types, contrast reduction helps to simulate areas of low lighting which can be expected in the dataset.)

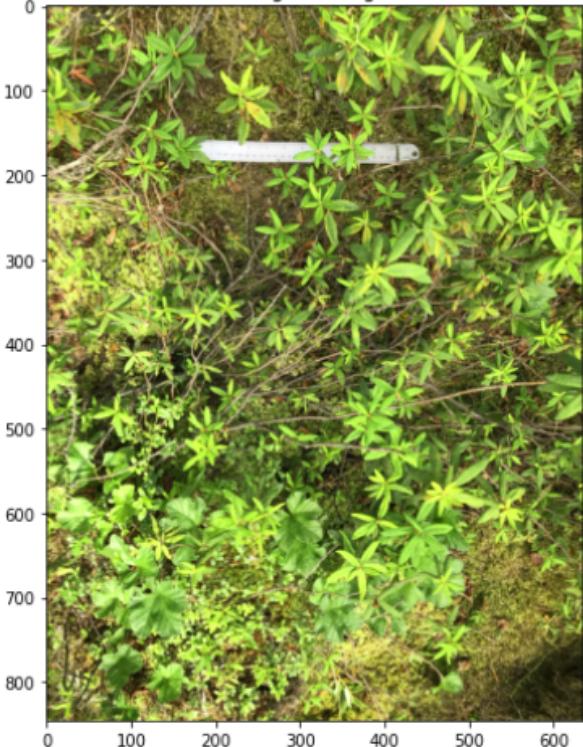
# Some training and testing details:

- No. of training samples: 1160
- Training time: ~ 66 hrs (100 epochs)
- Model inference time: ~ 3 secs (For image dimension: [635,846] )
- Device specs: Tesla K80 GPU (VRAM:12GB)
- ML Library: PyTorch

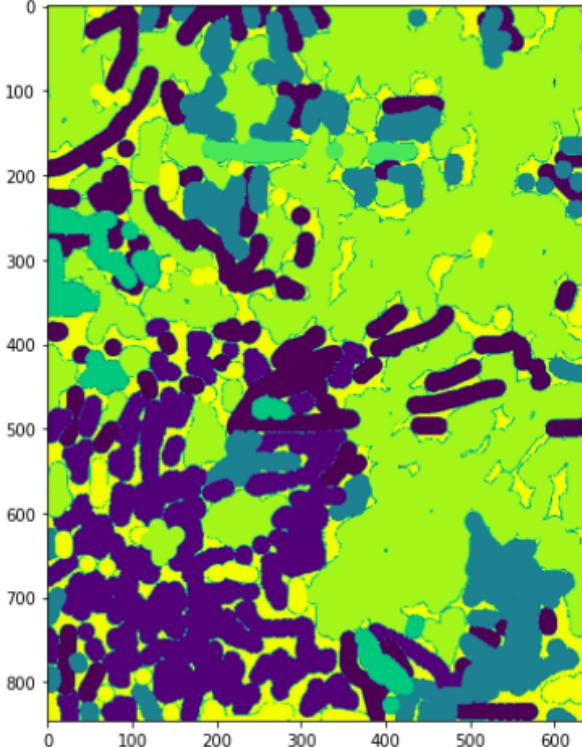
# Some results on validation images:



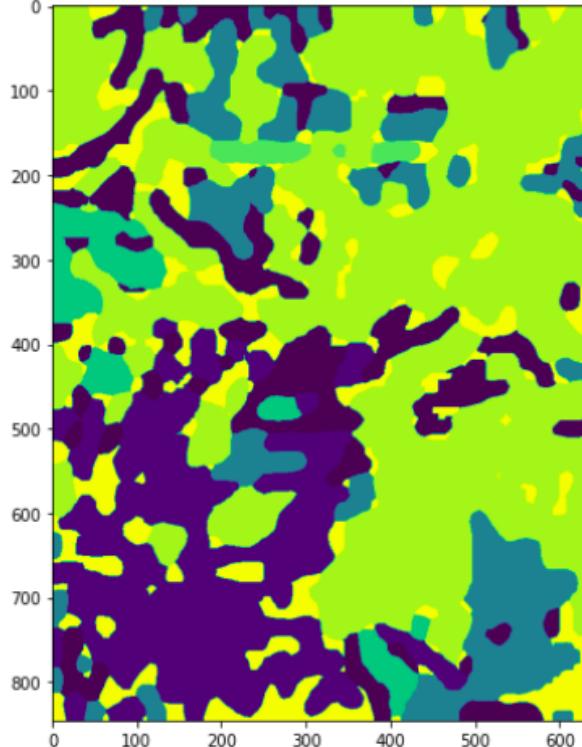
Original Image



Ground Truth Label



Predicted Label



# **Future Work:**

1. Compare our classification results against manual ground cover estimation calculations
2. Deploy autonomous drones to collect and analyze ground cover data in the field

*Thank you*