Deep Learning-Based Change Detection of Forest, Water, Barren Land, and Human Activity

There have been many studies that use deep learning techniques to monitor land use [1], forest coverage [2], and desertification [3]. Previous studies have also used deep learning-based change detection to monitor urban forest cover change [4]. This study aims to perform change detection of forest, water, barren land, and human activity by using deeply supervised image fusion network (DSIFN) [5] to create change maps and Deeplabv3 model fine-tuned for image segmentation [6].

Keywords: deep learning; transfer learning; forest cover change detection; river change detection; barren land detection; very high resolution (VHR); DeepLabv3+; deeply supervised image fusion network (DSIFN); desertification

Expected output

- Change map of a region based on pre- and post-change VHR satellite image of region.
- Grayscale segmented 2D map of an urban region, based VHR satellite image, classes include forest, water, barren land, and human activity (buildings, roads, agriculture).

Potential use

- Forest conservation:
    - Monitoring.
    - Intervention impact analysis.
- Urban planning:
    - City growth.
- Desertification identification:
    - Monitoring.
    - Intervention impact analysis.

Datasets

- LoveDA https://github.com/Junjue-Wang/LoveDA [7]

- Change Detection Dataset
  https://drive.google.com/file/d/1GX656JqqOyBi_Ef0w65kDGVto-nHrNs9 [8]

Unexplored Datasets

- Sourcing from Google Earth Engine GEE
  https://earthengine.google.com/

Data Preparation

1. LoveDA [7]

Category labels: background – 1, building – 2, road – 3, water – 4, barren – 5, forest – 6, agriculture – 7. And the no-data regions were assigned 0 which should be ignored. The provided data loader will help you construct your pipeline.

Original image and mask:

Merged labels:

- Forest: 6 -> 1 (Bright Green)
- Water: 4 -> 2 (Bright Blue)
- Barren land: 5 -> 3 (Bright Orange)
- Human activity: 2, 3, 7 -> 4 (Bright Magenta)
- Background: 1 -> 5 (Gray)

- No-data: 0 -> 0 (Black)

Image ‘1366’ from train dataset:

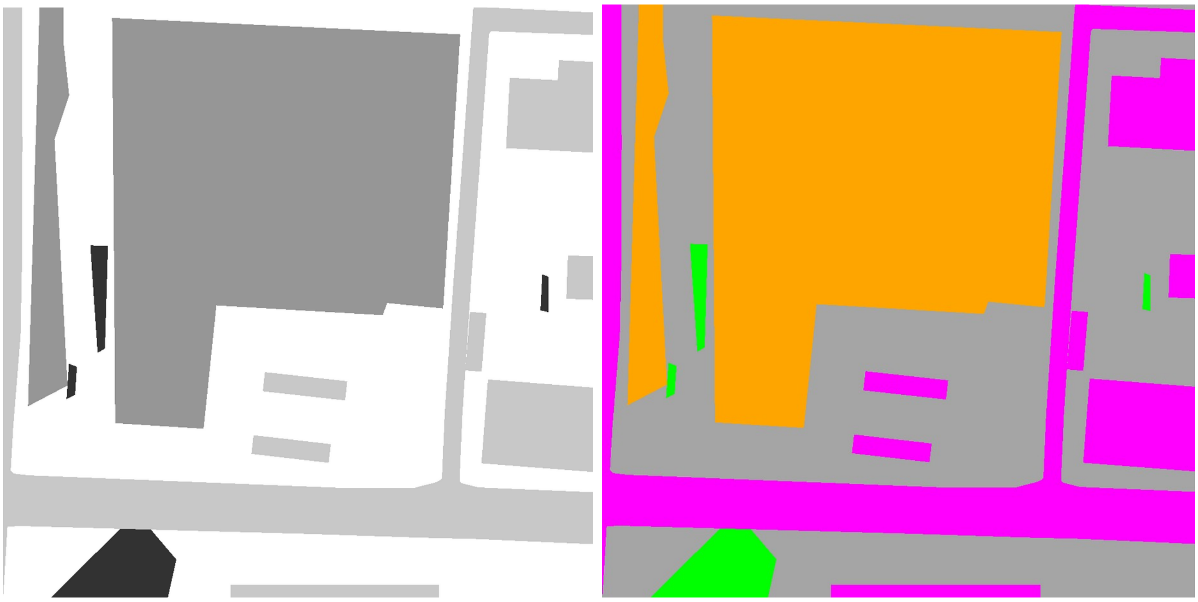
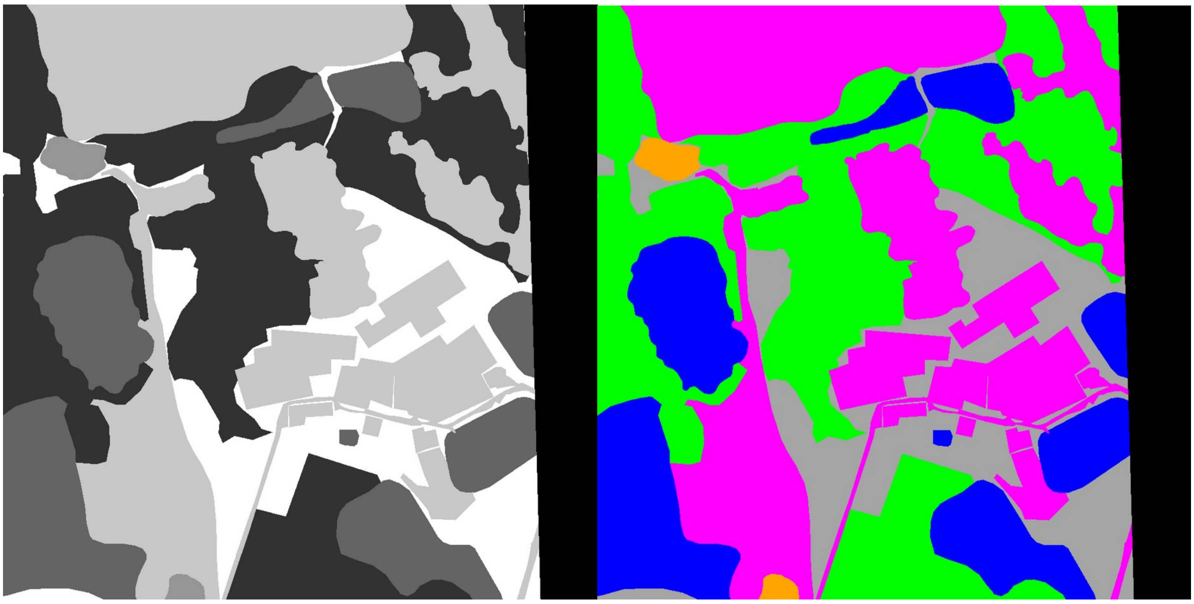


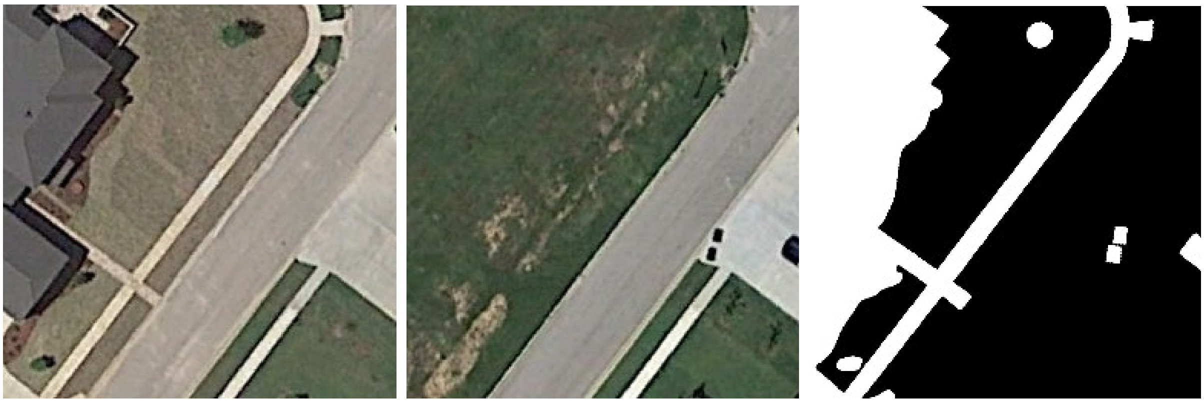
Image ‘3520’ from validation dataset:



Processed dataset:
https://drive.google.com/drive/folders/1AX5DdNeSseyn3rN89jYoNEznxX7QCUgH?usp=sharing

2. Change Detection Dataset (CDD) [8]

Image ‘19’ from Real/subset/train. From left to right, A-B-OUT.



Transfer learning

1. DeepLabv3+ [6,9]

Using model weights from PyTorch [Deeplabv3-ResNet-101](). Trained fro 20 epochs, on LoveDA [7].

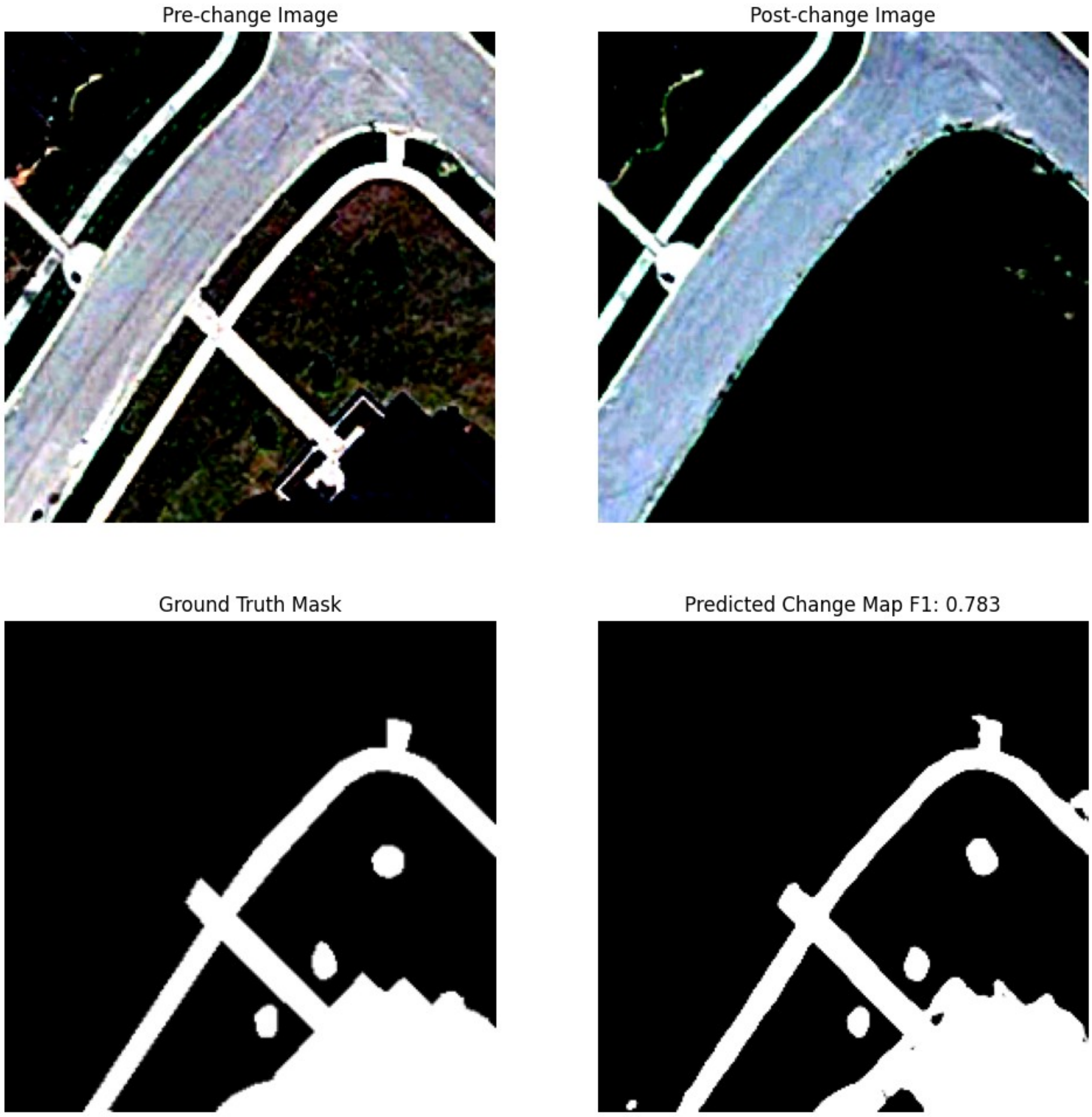
2. VGG16

No additional fitting is done. Model up to pool5 is used for feature extraction [10].

Deeply Supervised Image Fusion Network (DSIFN) Trained for 50 epochs on CDD [8].

Trained model:
https://drive.google.com/file/d/1FvhzXGa9grV2fcWcrTcKyfRg9HVwf81y/view?usp=sharing

Generated Change Maps



Validation

On validation set (2998 samples), model achieved mean F1 score of 0.65466. This might be due to limited training time and variation in training dataset. Variation in training dataset can be increased with the use of transforms in PyTorch.

Generated Urban Activity Segmentation

Reference

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