

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:

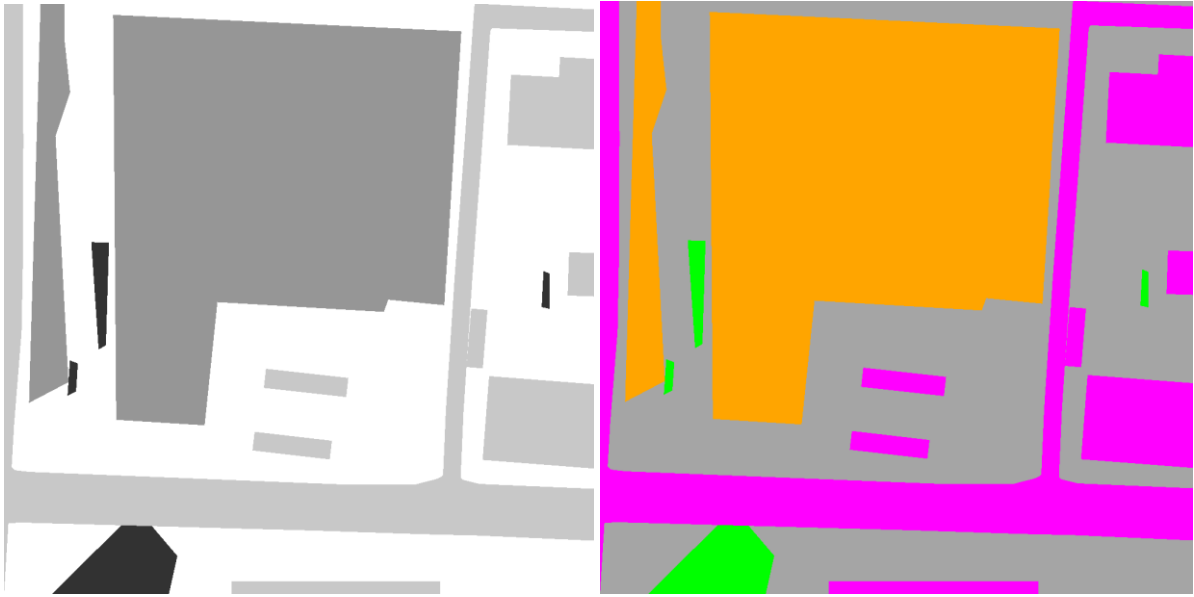
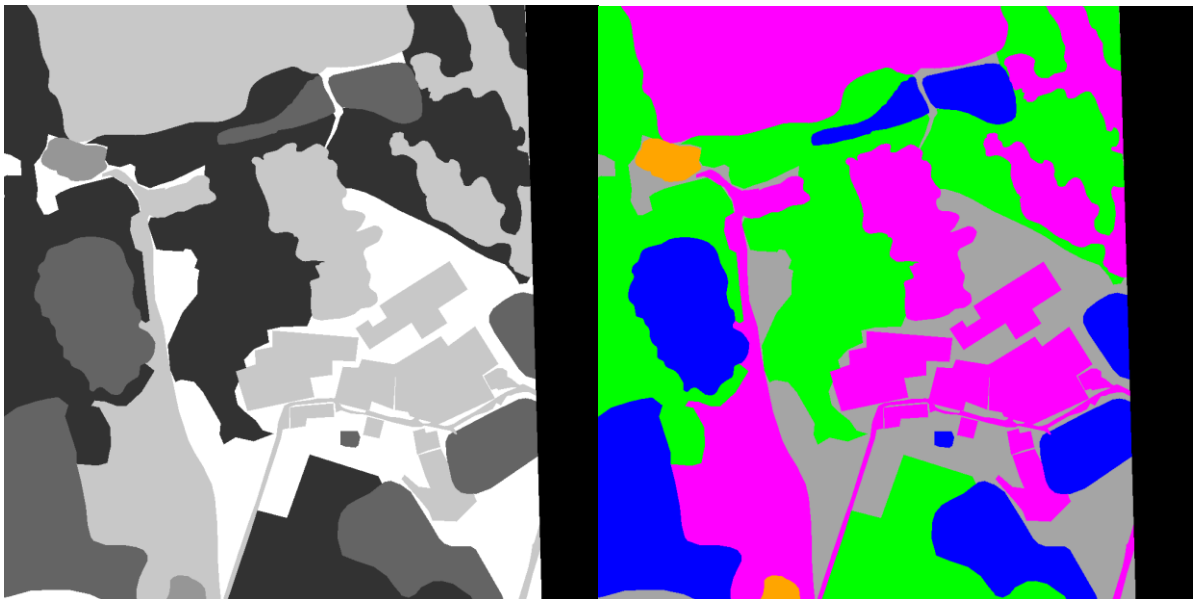


Image '3520' from validation dataset:



Processed dataset:

<https://drive.google.com/drive/folders/1AX5DdNeSseyN3rN89jYoNEznxX7QCUgH?usp=sharing>

2. Change Detection Dataset (CDD) [8]

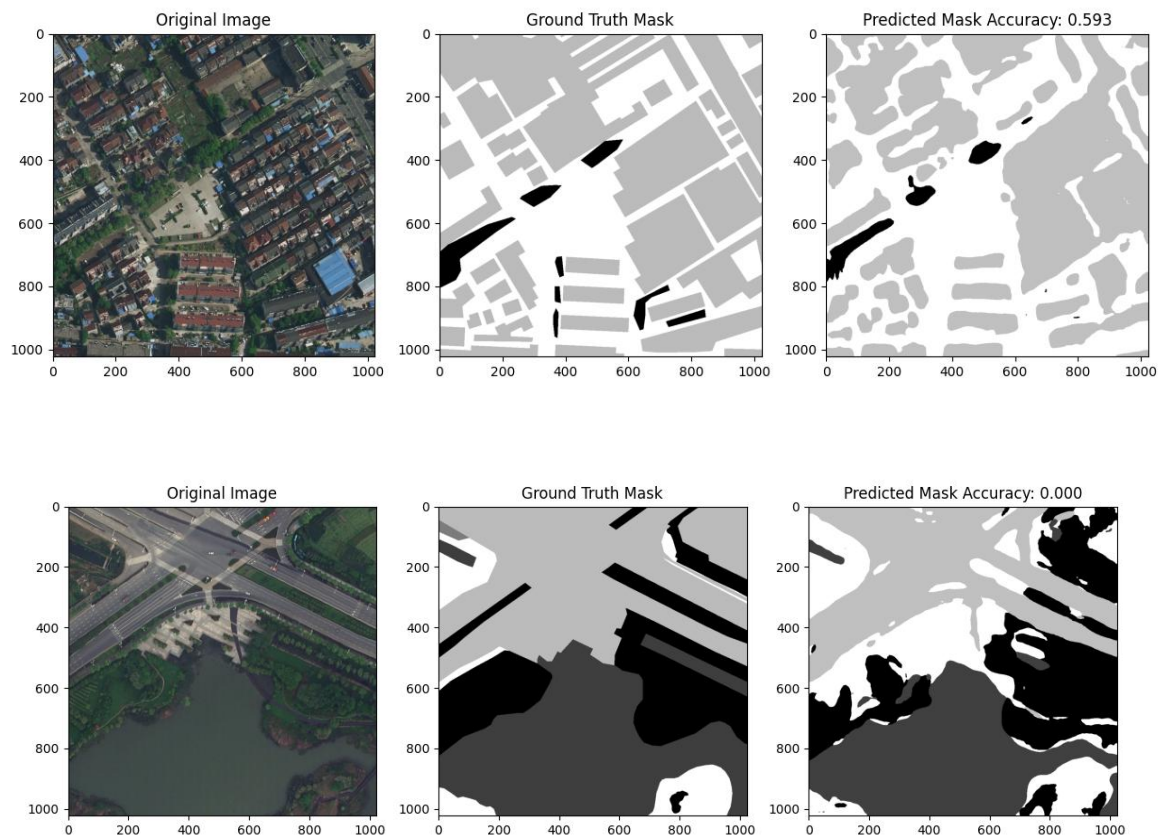
Image '19' from Real/subset/train. From left to right, A-B-OUT.



Transfer learning

1. DeepLabv3+ [6,9]

Using model weights from PyTorch [DeepLabv3-ResNet-101](#). Trained for 20 epochs, on LoveDA [7]. After 20 epochs of training, DeepLabv3+ model is unable to produce sharply segmented masks with the 6 different classes. This might be due to the similarities in features such as grass/agriculture with forest, and small structures with background. A potential addition to the current model is to use attention layers, or to rethink the class grouping in the dataset.



2. VGG16

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

Deeply Supervised Image Fusion Network (DSIFN)

VGG16 [10] is used as a feature extractor for pre- and post-change VHR satellite image then the extracted deep features are fed into a deeply supervised difference discrimination network (DDN) for change detection, [4,5]. The DDN uses Channel Attention Modules (CAM) to emphasize important channels, and Spatial Attention Modules (SAM) to allow network to approach the changed regions faster [5]. Trained for 50 epochs on CDD [8].

Trained model:

<https://drive.google.com/file/d/1FvHzXGa9grV2fcWcrTcKyfRg9HVwf81y/view?usp=sharing>

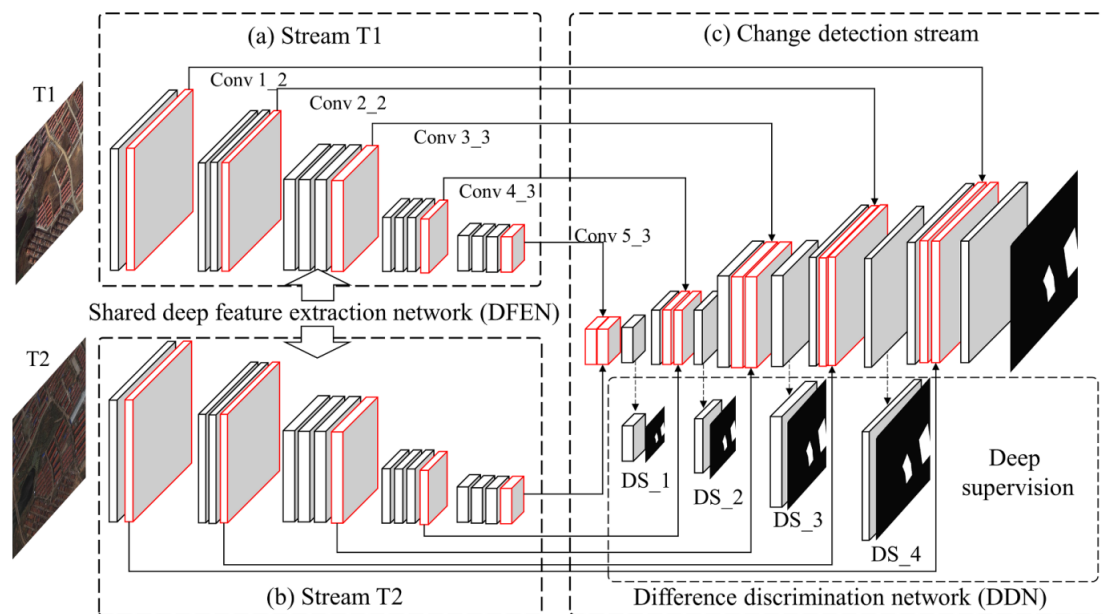
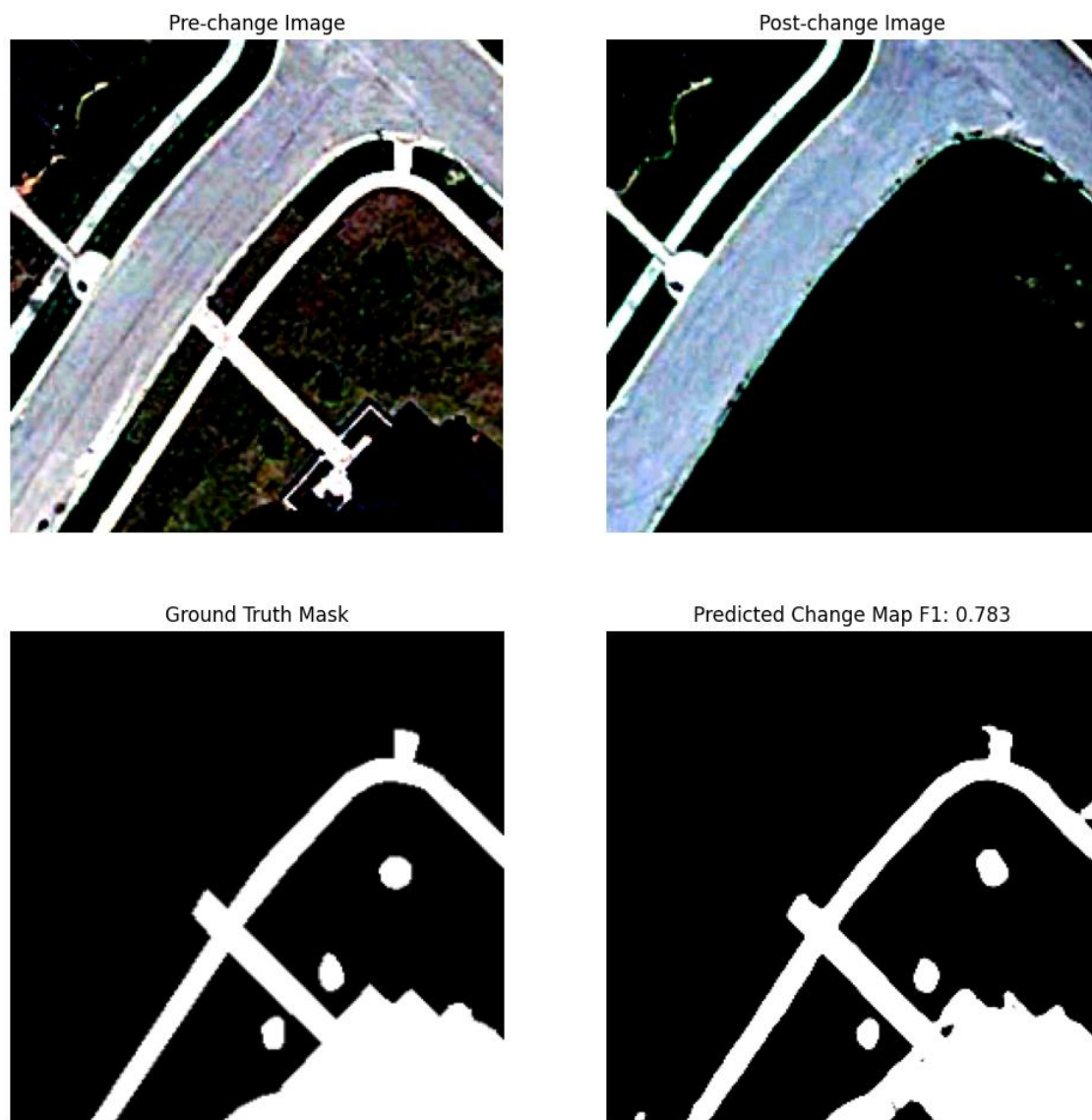


Figure 1: Image Fusion Network (IFN) architecture implemented in code. Image taken from [5]

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.

Reference

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