Unsupervised Change Detection in Satellite Images Using Convolutional Neural Networks

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Introduction

- Image change detection is a process of high interest among researchers that has many uses in many different fields such as military, business, agriculture, etc.

- In our project, we are focussing on the change detection in high resolution satellite images.

Introduction Continued

- Previously, methods for change detection were classifying contents of two temporally different images and then compare the classified images to detect change.
- Resource and time consuming, Needs high accuracy for classification. Errors in classification in one image reflects globally.
- We need a method that overcomes the disadvantages and is computationally cheap.

Introduction Continued

The paper under our consideration [de Jong, Kevin Louis, and Anna Sergeevna Bosman. "Unsupervised Change Detection in Satellite Images Using Convolutional Neural Networks." 2019 International Joint Conference on Neural Networks (IJCNN). IEEE, 2019.] proposed -

- New method for constructing Difference Image (DI)
- We used trained CNNs for semantic segregation.
- We create DI with the help of feature maps from the CNNs.
- Classify nature of change in the DI, segregating into three labels- buildings, roads/parking lot and everything else remaining.

Related Work

- Gong et al. [16] have employed DNNs for change detection. DNNs have the ability to extract a compressed hierarchical feature representation of an image, which enables a meaningful semantic comparison of temporally different images.

- Another study by Gong et al. [12] make use of unsupervised feature learning performed by a CNN to learn the representation of the relationship between two images. The CNN is then fine-tuned with supervised learning to learn the concepts of the changed and the unchanged pixels.

Related Work

- O. Yousif et al.[13] investigated a nonlocal means (NLM) denoising algorithm that combines local structures with a global averaging scheme in the context of change detection using multitemporal SAR images. Both visual and quantitative analyses have proven the efficiency of the PCA-NLM algorithm in improving urban change detection using multitemporal SAR images.

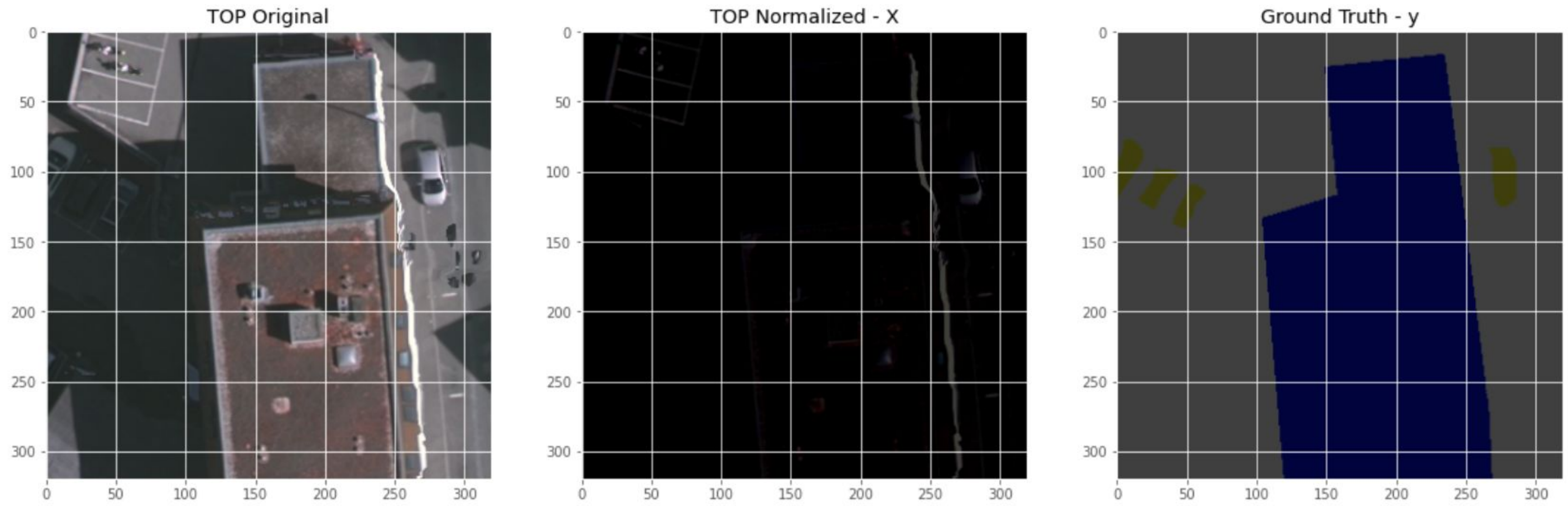
Methodology

Dataset

- Vaihingen dataset - provided by International Society for Photogrammetry and Remote Sensing (ISPRS).
- 33 Satellite image segments of different sizes each consisting of True Orthophoto (TOP) extracted from larger TOP.
- 16 segments provided with ground truth. We used 15 images for training and 1 for testing.
- Images are of urban area with buildings and roads.

Preprocessing

1. Images were cut into 320x 320 segments
2. Normalized to have mean 0.5 and std 0.5



U-Net for Semantic Segmentation

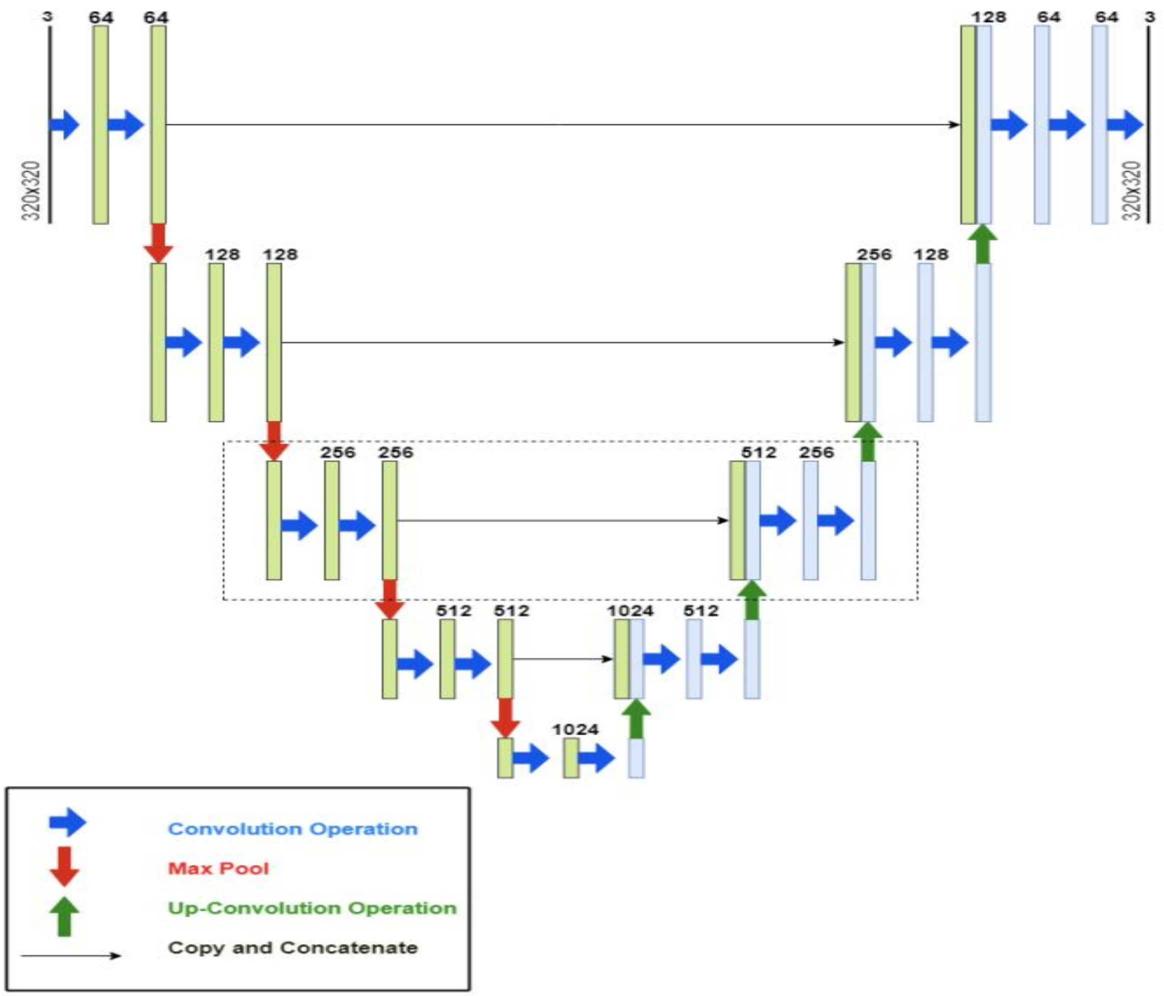


Fig. 1. U-net architecture used in this study.

U-net Parameters

- **Encoders**
  - Convolution at every layer followed by batch normalization.
  - Convolution layers - Kernel size- 3*3, stride 1, padding 1
  - Max Pooling Layers - Kernel size- 3*3, stride 2, padding 0 for max
- **Decoders**
  - Deconvolution - Kernel size- 3*3, stride 2, padding 0, followed by batch normalization
- Hidden layers used the leaky ReLU activation function with the negative slope of 0.2,
- Softmax function was used in the output layer.
- Argmax applied on output

Training

- 601 images with size 320x320x3
- Adaptive moment estimation of gradient descent.
- Why?- Requires less tuning of parameters.
- **Parameters**
  - batch size - 4
  - Loss function- Log loss
  - Total epochs = 20
  - Learning rate= 0.0002

Differential Image Generation Algorithm

- Algorithm : input - two m*m images. Initialize the difference image with zeros. Then -

for i=1 to m do:
for j=1 to m do:
if $f2_{ij} - f1_{ij} > t$:
$D_{ij} = f2_{ij}$

- We used empirically obtained threshold values that were used in the paper which depend on activation function of model and exposure levels of images.
- **Thresholds:** E1 - 0.4, E2 - 0.6, E3 - 0.8, E4 - 1.0, E5 - 1.2

Change Detection

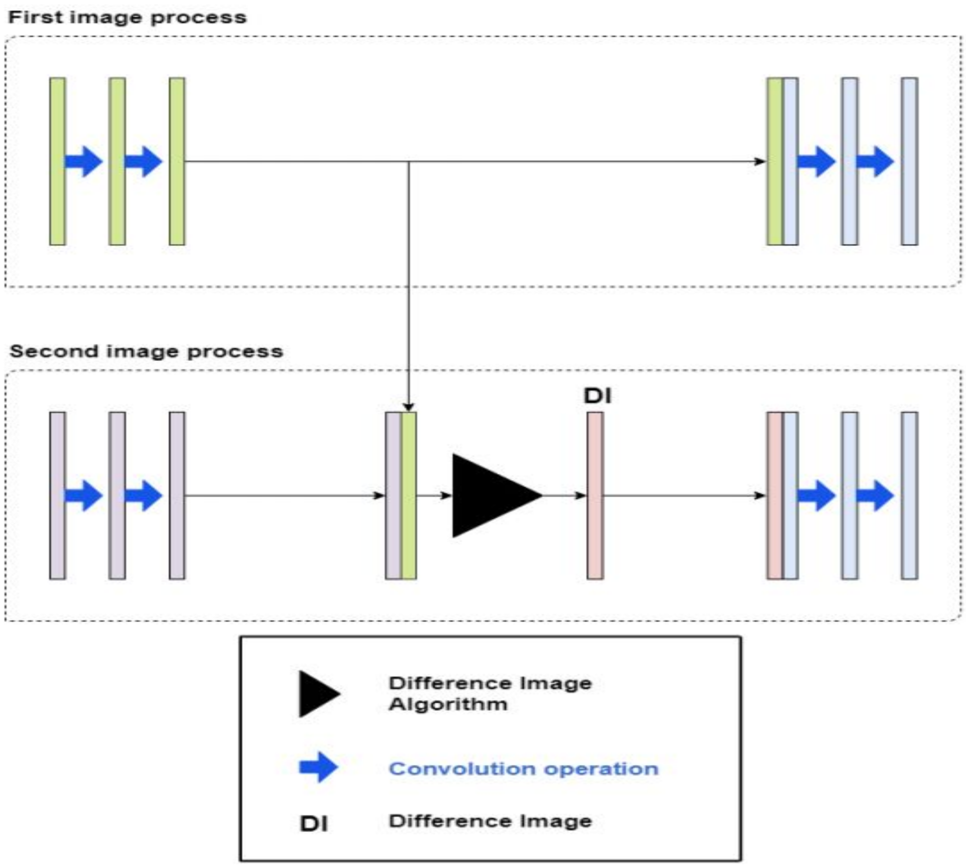


Fig. 2. Inference phase: two images are processed concurrently for the purpose of generating the corresponding DI.

Evaluation

1. Was the changed detected?

PCC1 = (TP+TN)/(TP+TN+FP+FN)

***TP= True positive, TN= True Negative, FP= False Positive, FN= False Negative**

2. Was changed pixels labeled correctly?

PCC2 = Correctly classified pixels / Total pixels

Implementation

- Language and Libraries-
  - Python 3.6 with Jupyter Notebook
  - Pillow (PIL) - Reading Images
  - Matplotlib - Visualization
  - Numpy - Array manipulation
  - Math - Array manipulation
  - Tensorflow.Keras - Design and train U-Net.
  - Scikit-learn.metrics - Evaluation

Difference from the Paper in implementation

- Mostly followed the paper.
  - skipped padding 0 to avoid data loss.
  - We used 80% images for training and 20% for validation.

Evaluation

- **Test Data**
  - From our single test image, we had 36 images after augmentation.
  - Evaluated semantic segmentation on 12 images (12*320*320 pixels)
    - The images include
      - **Immutable Terrain [roads, driveways, parking lots - class 0 (red)]**
      - **Background [vegetation, cars, others - class 1(green)]**
      - **buildings[class 2 (blue)].**

Evaluation

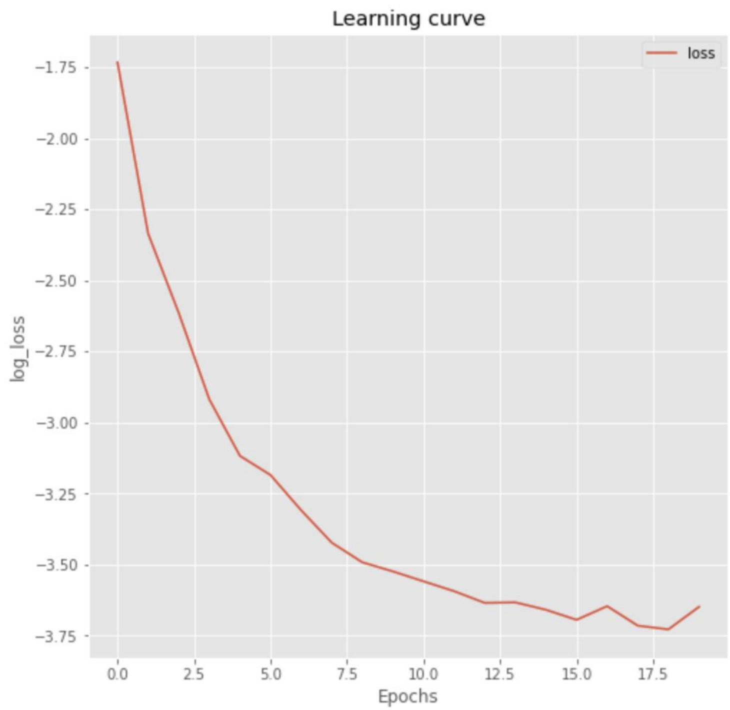
- **Evaluation of Change Detection**
  - No temporal images of same scene in dataset, hence created 6 simulated images from 2 test images.

1. 5% change
2. 10% change
3. 20% change
4. 5% change + GN of variance 10
5. 5% change + GN of variance 20
6. 5% change + GN of variance 40

****GN - Gaussian Noise****

Results

- **Evaluation of semantic segmentation-**
  - Validation accuracy- 87% at epoch 20. The Paper reported 89% at epoch 15.
  - 6-7 Hours for training.
  - Low accuracy for background because less instances in this class and less differentiable features.

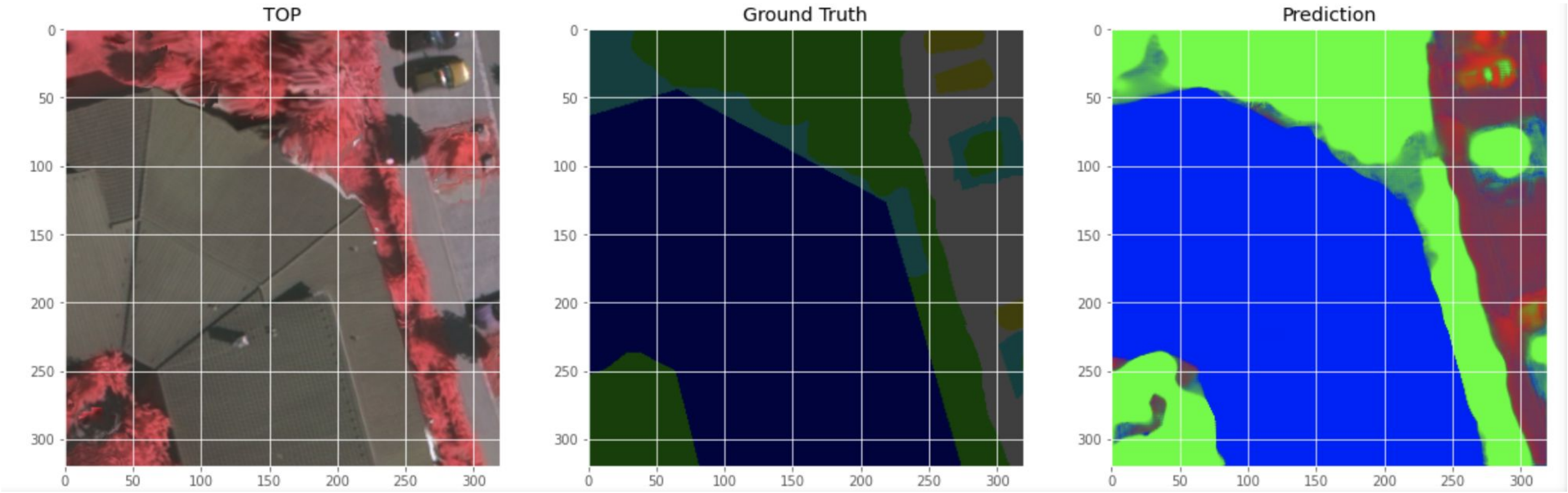


Results

- **Evaluation of semantic segmentation on test data**

	Class Label	Color Label	PCC1
Immutable Terrain	0	Red	84.0%
Background	1	Green	71.8%
Buildings	2	Blue	91.6%
Overall	-	-	82.9%

Visualization of Semantic Segmentation



Results Continued

- **Evaluation of change detection**

Pixels Changed	**PCC1**	**PCC2**
5%	99.2%	87.9%
10%	97.8%	61.5%
15%	85.6%	78.7%
Gaussian Noise Variance	**PCC1**	**PCC2**
10	99.3%	88.8%
20	99.2%	88.6%
40	99.2%	89.2%

Table 1 : Results we got

Pixels Changed	$PCC1$	$PCC2$
5%	91.2 %	93.0 %
10%	88.7 %	91.2 %
15%	87.5 %	90.7 %
Gausian variance	$PCC1$	$PCC2$
10	91.0 %	92.0 %
20	86.2 %	89.2 %
40	81.5 %	85.4 %

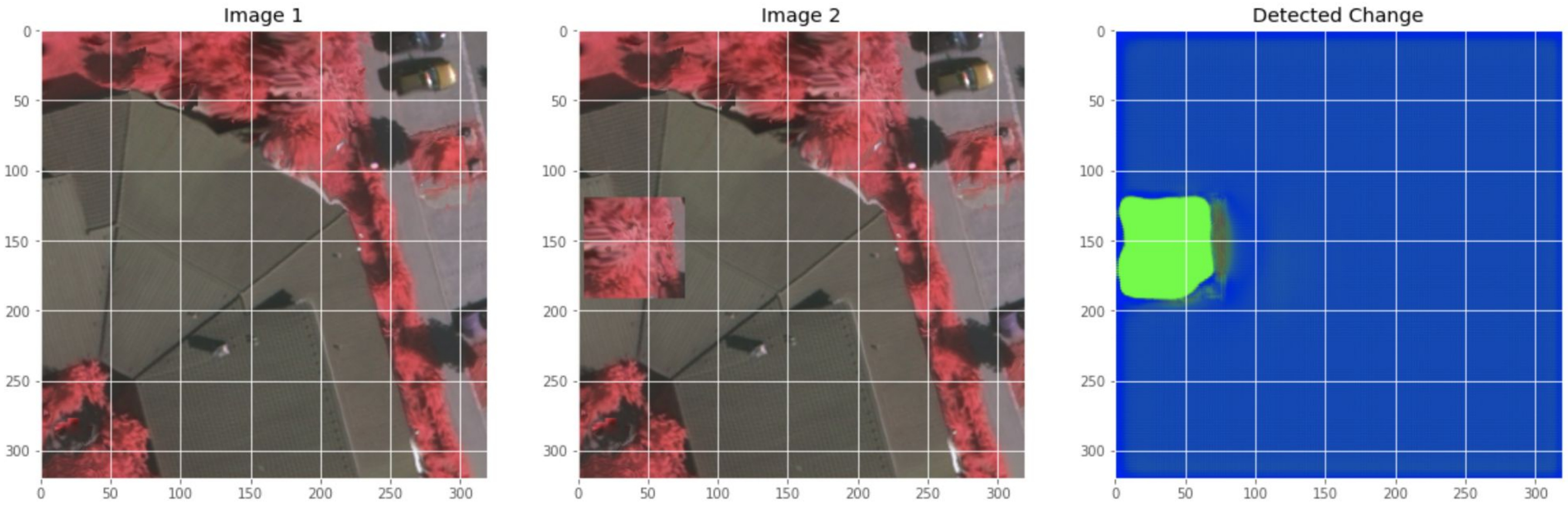
Table 2 : Results Reported in the paper

Visualization of Test Cases

Test case 1 : 5% change

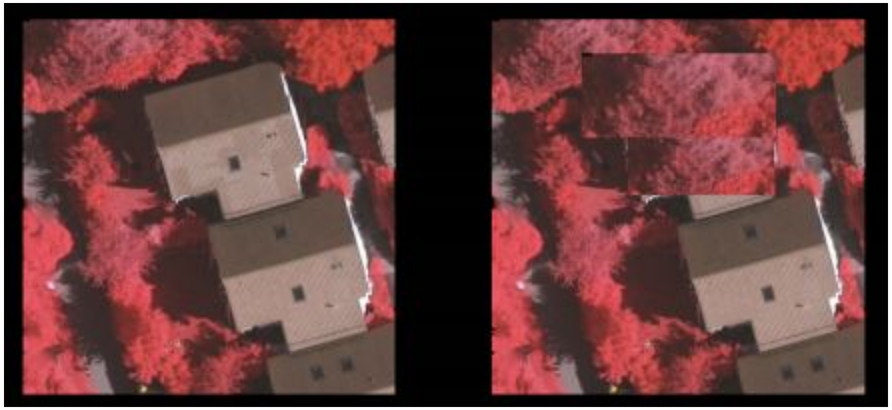
PCC1 : 99.2%

PCC2 : 87.9%

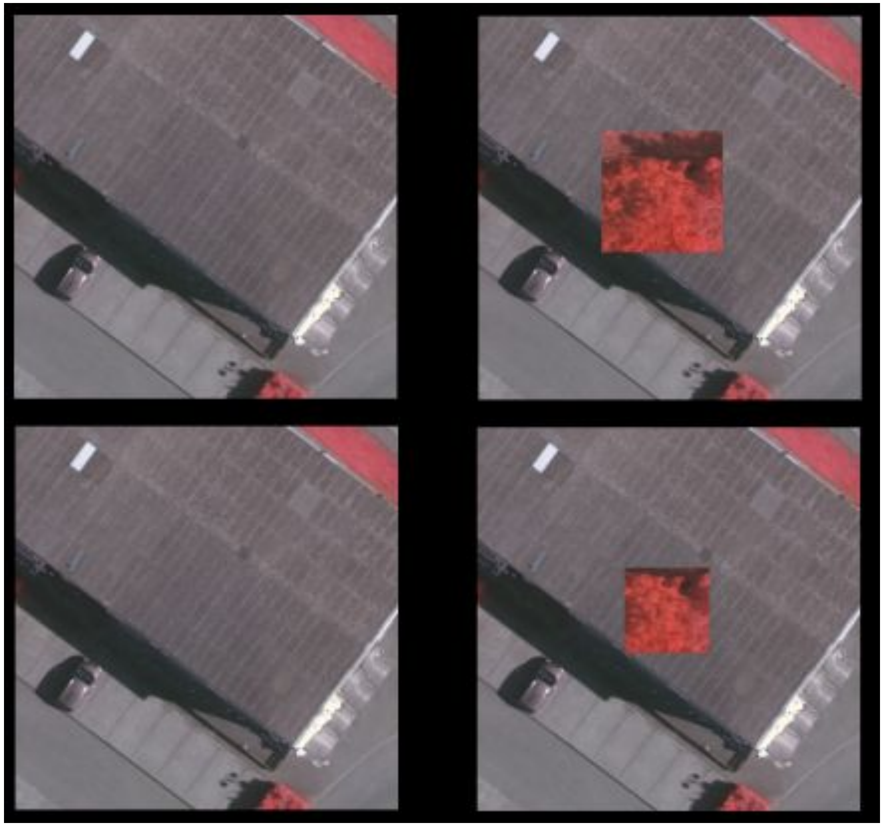


Evaluation of Change detection

Test Cases 2 and 3 in the paper - contained uniform changes



Test Case 3



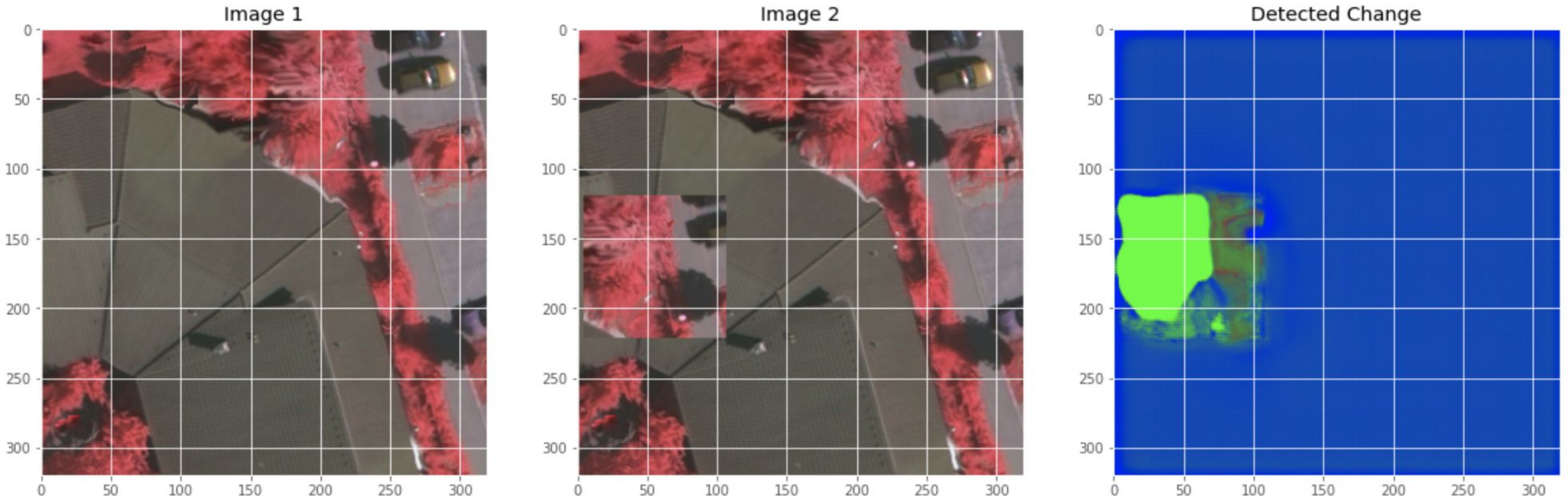
Test Case 1 and 2

Visualization of Test Cases

Test case 2 : 10% change

PCC1 : 97.8%

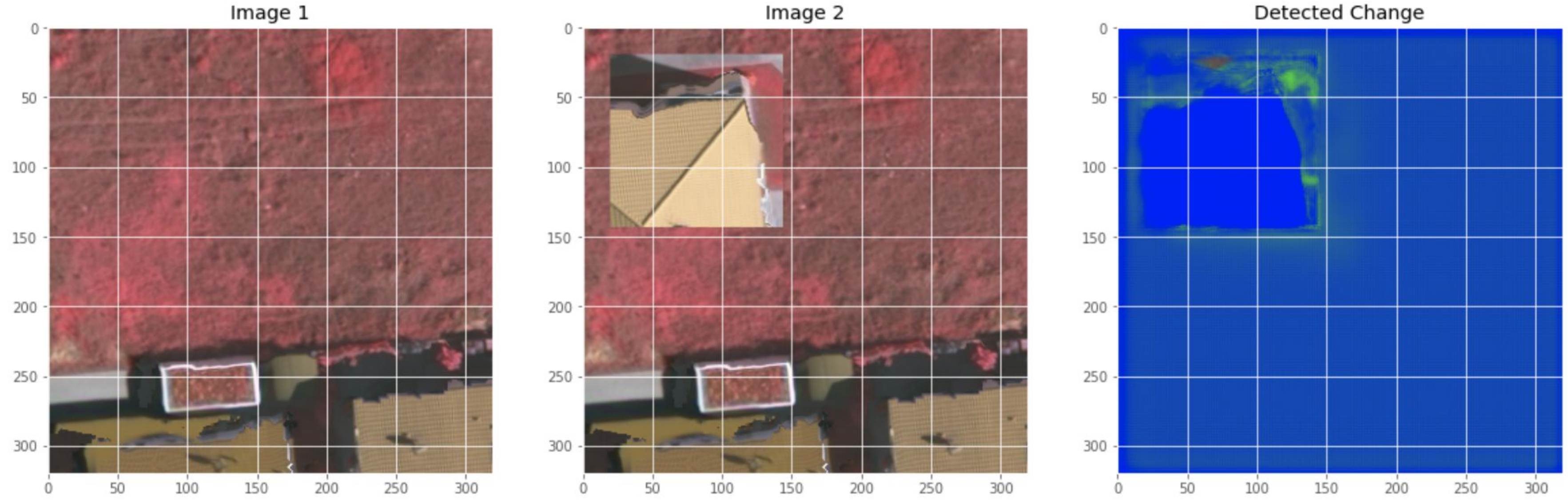
PCC2 : 61.5%



Visualization of Test Cases

Test case 3 : 15% change

PCC1 : 85.6%
PCC2 : 78.7%

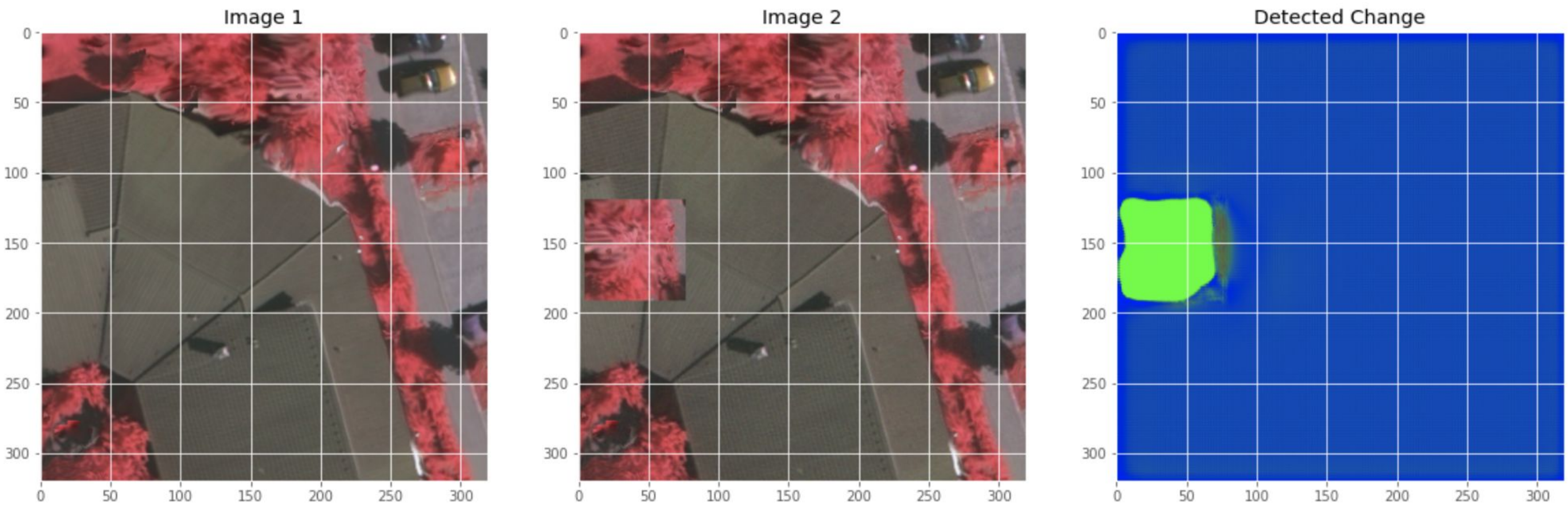


Visualization of Test Cases

Test case 4 : 5% change + Gaussian Noise with variance 10

PCC1 : 99.3%

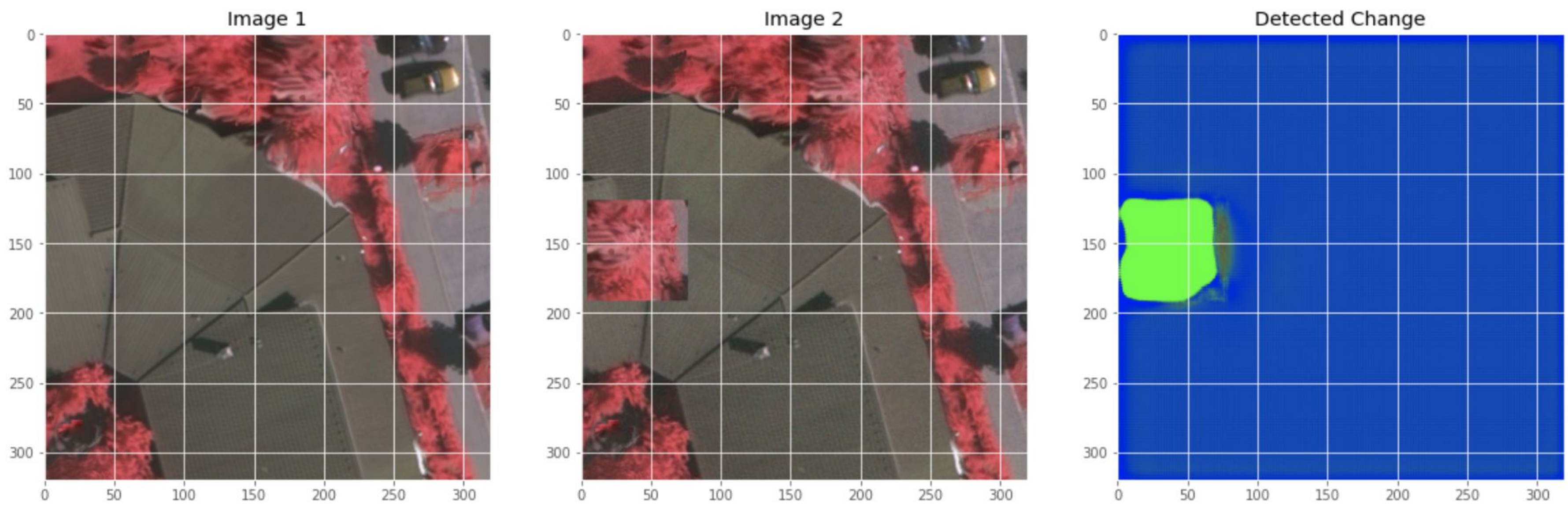
PCC2 : 88.8%



Visualization of Test Cases

Test case 5 : 5% change + Gaussian Noise of Variance 20

PCC1 : 99.2%
PCC2 : 88.6%

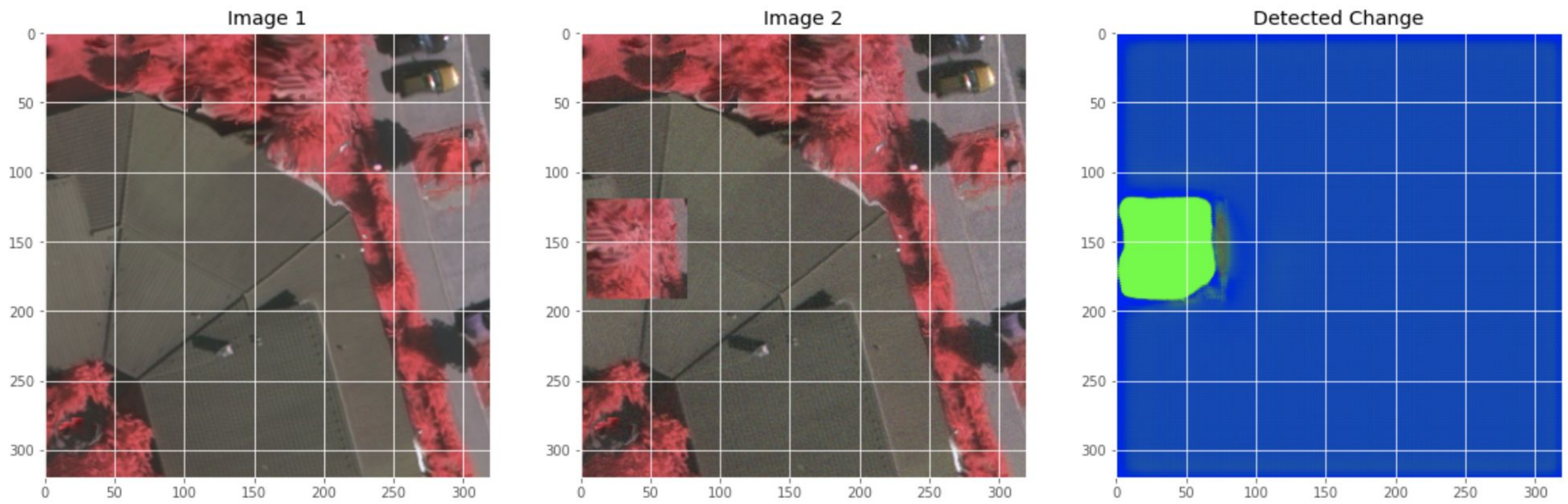


Visualization of Test Cases

Test case 6 : 5% change + Gaussian Noise of Variance 40

PCC1 : 99.2%

PCC2 : 89.2%



Conclusion

- Finding a library for correct preprocessing is a very crucial task. Because different libraries support the same task, but they handle images differently. Ex- OpenCV does not support .tif files.
- Unsupervised method for change detection in satellite images.
- Trained U-Net struggles near the boundary.

Future Work

- Parameter tuning for U-net was left for future work with respect to the threshold values used.
- The dataset chosen was small and has to be checked over a larger one.
- We simulated changes in the dataset for making temporal images and thus data with real changes is to be tested.
- Noise sources like elevation, reflection, camera angles and environmental causes like sunlight and clouds need to be considered and worked upon.

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