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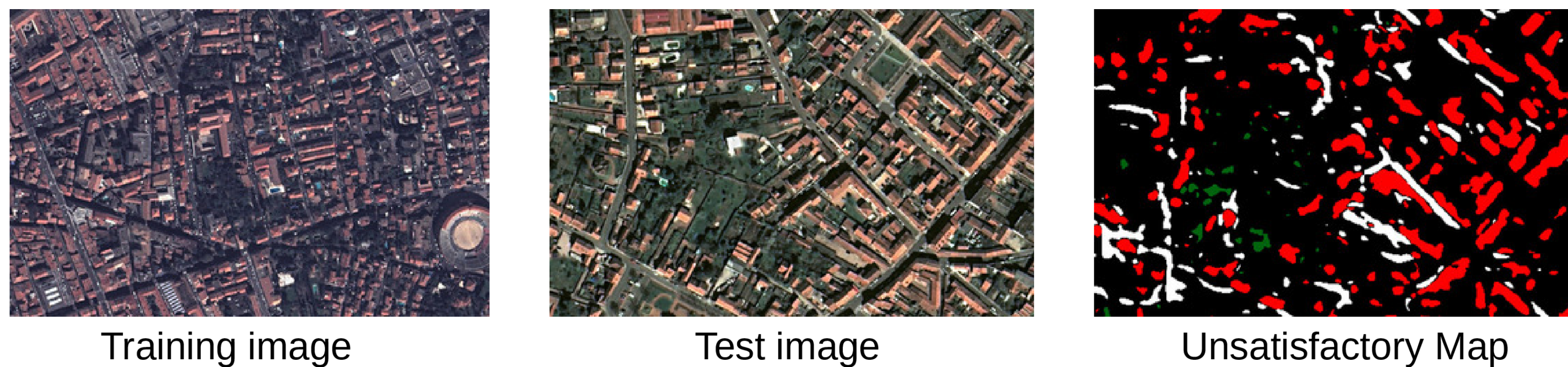
# DATA AUGMENTATION BY GENERATIVE ADVERSARIAL NETWORKS FOR SEMANTIC SEGMENTATION OF SATELLITE IMAGES

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## PROBLEM DEFINITION

- Semantic segmentation consists in assigning a correct class label to each pixel in the image.
- Semantic segmentation of satellite images is a crucial step for automatic map generation. Training a Convolutional Neural Network (CNN) on an annotated set, and using the trained CNN to automatically generate maps for new satellite images is a common approach.
- CNNs generate unsatisfactory maps when training and test images look significantly different.



Training image

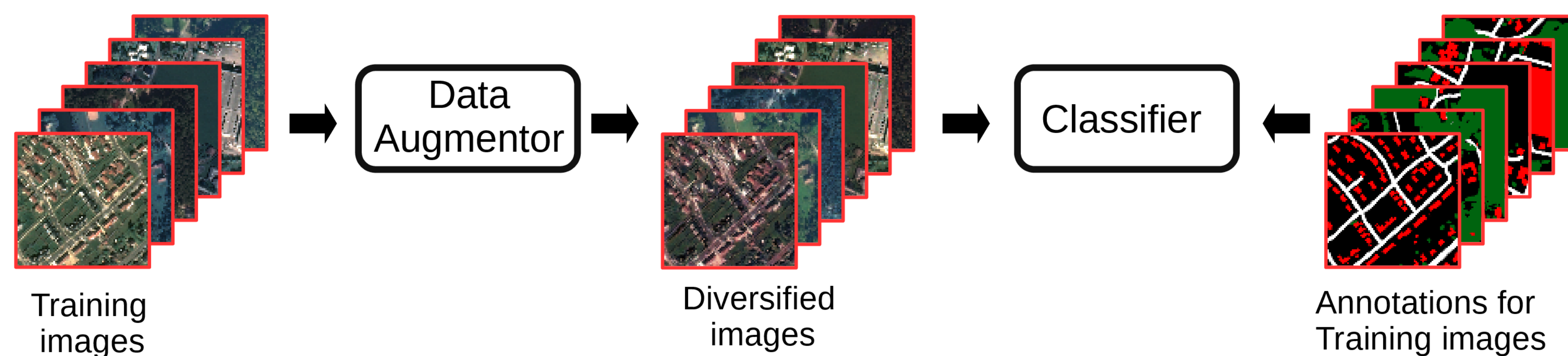
Test image

Unsatisfactory Map

- Changing contrast, brightness, etc. of the images in the training stage is a common data augmentation approach to better generalize CNNs [1, 2]. However, when training and test images have largely different color distributions, these augmentation methods cannot yield an excellent performance.

## TRAINING A CLASSIFIER WITH THE DATA AUGMENTOR

- We propose to use Generative Adversarial Networks (GANs) for better data augmentation by performing style transfer between images.
- Our proposed learning method consists of a data augmentor and a classifier.
- In each training iteration, the data augmentor, which is a GAN, can stylize each image as one of the randomly selected training and test images. We call this operation random diversification. The diversified images are then used to train the classifier.



- In the first stage, we train the data augmentor to be able to stylize each image like any other. In the second stage, we freeze the data augmentor and train the classifier.
- The data augmentor allows the classifier to learn from data that is representative for both training and test images.
- More details can be found in our papers related to GAN based data augmentation by performing style transfer between satellite images [3, 4, 5, 6].

## STYLE TRANSFER BETWEEN MULTIPLE SATELLITE IMAGES

- Leibnitz, Bad Ischl, and Vaduz are test cities, the others are used for training.
- The cells in yellow represent real images, the others are fake images generated by our data augmentor.



- Since the data augmentor enables the classifier to learn from data that is similar to those of each training and test images, the classifier generates much better maps.

IoU scores for each class when we train a classifier without (top) and with (bottom) the data augmentor.

				Bad Ischl				Vaduz				Leibnitz				
	Build.	Road	Tree	Ovr.	Build.	Road	Tree	Ovr.	Build.	Road	Tree	Ovr.	Build.	Road	Tree	Ovr.
	51.86	39.33	79.80	56.99	38.04	34.33	75.88	49.42	2.29	1.13	0.04	1.15	43.31	34.28	73.18	50.26
	60.52	53.08	82.87	65.49	53.03	39.44	71.77	54.75	43.31	34.28	73.18	50.26	43.31	34.28	73.18	50.26

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