TorchSat

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Contents:

TorchSat is an open-source deep learning framework for satellite imagery analysis based on PyTorch.

This project is still **work in progress**. If you want to know more about it, please refer to the Roadmap .

Hightlight

- Support multi-channels(> 3 channels, e.g. 8 channels) images and TIFF file as input.
- Convenient data augmentation method for classification, sementic segmentation and object detection.
- Lots of models for satellite vision tasks, such as ResNet, DenseNet, UNet, PSPNet, SSD, FasterRCNN ...
- Lots of common satellite datasets loader.
- Training script for common satellite vision tasks.

CHAPTER 1

Installation

1.1 Deepndencies

TorchSat is based on PyTorch, so you should install the PyTorch first. And if you want to use the GPU version, you should install CUDA.

Python package dependencies(seee also requirements.txt): pytorch, torchvision, numpy, pillow, tifffile, six, scipy, opencv

> Note: TorchSat only suport Python 3. We recommend version after Python 3.5(including python 3.5), but wo have not tested any version below Python 3.5

1.2 Install

1.2.1 Install from PyPI

- PyPI: `pip3 install torchsat`

1.2.2 Install from source

- Install the latest version

```
git clone https://github.com/sshuair/torchsat.git
cd torchsat
python3 setup.py install
```

- Install the stable version
  1. Visit the release page and download the version you want.

2. Decompress the zip or tar file.
3. Enter the torchsat directory and run this command `python3 setup.py install`.

1.2.3 Docker

You can pull the docker image from Docker Hub if you want use TorchSat in docker.

1. pull image
   - cpu: `docker pull sshuair/torchsat:cpu-latest`
   - gpu: `docker pull sshuair/torchsat:gpu-latest`
2. run container
   - cpu: `docker run -ti --name <NAME> sshuair/torchsat:cpu-latest bash`
   - gpu: `docker run -ti --gpu 0,1 --name <NAME> sshuair/torchsat:gpu-latest bash`

This way you can easily use the TorchSat in docker container.

CHAPTER 2

Core Conceptions

Because TorchSat is based on PyTorch, you'd better have some deep learning and PyTorch knowledge to use and modify this project.

Here are some core conceptions you should know.

1. All input image data, Whether it is PNG, JPEG or GeoTIFF, will be converted to NumPy ndarray, and the ndarray dimension is `[height, width]` (single channel image) or `[height, width, channels]` (multi-channel image).
2. After the data is read into NumPy ndarray, there are only three data types, `np.uint8`, `np.uint16`, `np.float`. These three data types are chosen because, in satellite imagery,
    - The most common image stored in JPEG or PNG (such as the Google Map Satellite Image) is mostly `8-bit (np.uint8)` data;
    - And the `16-bit (np.uint16)` is mostly the original data type of remote sensing satellite imagery, which is also very common;
    - The third type `float (np.float)` is considered, because sometimes, we will use remote sensing index (such as NDVI_) as features to participate in training. For this data we suppose all input data values range from 0 to 1.

CHAPTER 3

Image Classification

This is classification turtorial for satellite image. We will use sentinal-2 TCI data as an example. It cover from training data prepare, train the model, and predict the new files.

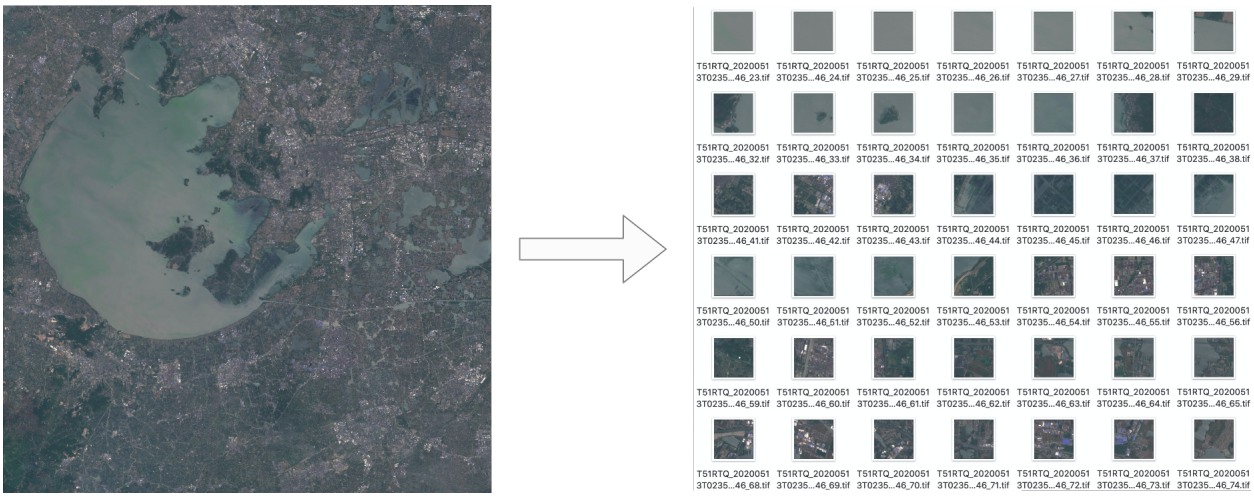
3.1 Prepare trainning data

Suppose we got a scene of sentinel-2 satellite TCI image data. You can download from esa scihub. I has got the secene id `T51RTQ_20200513T023551_TCI` and convert the JPEG2000 to GeoTIFF.

1. patch the large 10980x10980 pixel image to 128x128 pixel image

```
    cd  tests/classification/
    ts make-mask-cls --filepath T51RTQ_20200513T023551_TCI.tif --width 128 --height␣
↪128 --outpath ./patched
   processing 1/1 file T51RTQ_20200513T023551_TCI.tif ...
   14%|                                                                    | 12/85 [00:07
↪<00:45,  1.60it/s]
```

You should get the following data:



1. **labeling the train data and test data**

You can split the data into tran data and test data as below. And then labeling those patched image into four classes: `water`, `residential`, `farmland`, `forest`. Reorganize the catalog of these small images according to different categories and split them to train and validation dataset.

```
.
├── train
│   ├── water
│   │   ├── T51RTQ_20200513T023551_TCI_1_29.tif
│   │   ├── T51RTQ_20200513T023551_TCI_2_29.tif
│   │   └── ...
│   ├── frameland
│   │   ├── T51RTQ_20200513T023551_TCI_3_2.tif
│   │   ├── T51RTQ_20200513T023551_TCI_11_1.tif
│   │   └── ...
│   ├── residential
│   │   ├── T51RTQ_20200513T023551_TCI_0_29.tif
│   │   ├── T51RTQ_20200513T023551_TCI_1_37.tif
│   │   └── ...
│   ├── forest
│   │   ├── T51RTQ_20200513T023551_TCI_7_21.tif
│   │   ├── T51RTQ_20200513T023551_TCI_22_45.tif
│   │   └── ...
├── validation
│   ├── water
│   │   ├── T51RTQ_20200513T023551_TCI_5_32.tif
│   │   ├── T51RTQ_20200513T023551_TCI_5_12.tif
│   │   └── ...
│   ├── frameland
│   │   ├── T51RTQ_20200513T023551_TCI_9_2.tif
│   │   ├── T51RTQ_20200513T023551_TCI_6_76.tif
│   │   └── ...
│   ├── residential
│   │   ├── T51RTQ_20200513T023551_TCI_8_29.tif
│   │   ├── T51RTQ_20200513T023551_TCI_3_37.tif
│   │   └── ...
│   ├── forest
│   │   ├── T51RTQ_20200513T023551_TCI_8_12.tif
│   │   ├── T51RTQ_20200513T023551_TCI_31_5.tif
│   │   └── ...
```

3.2 Training model

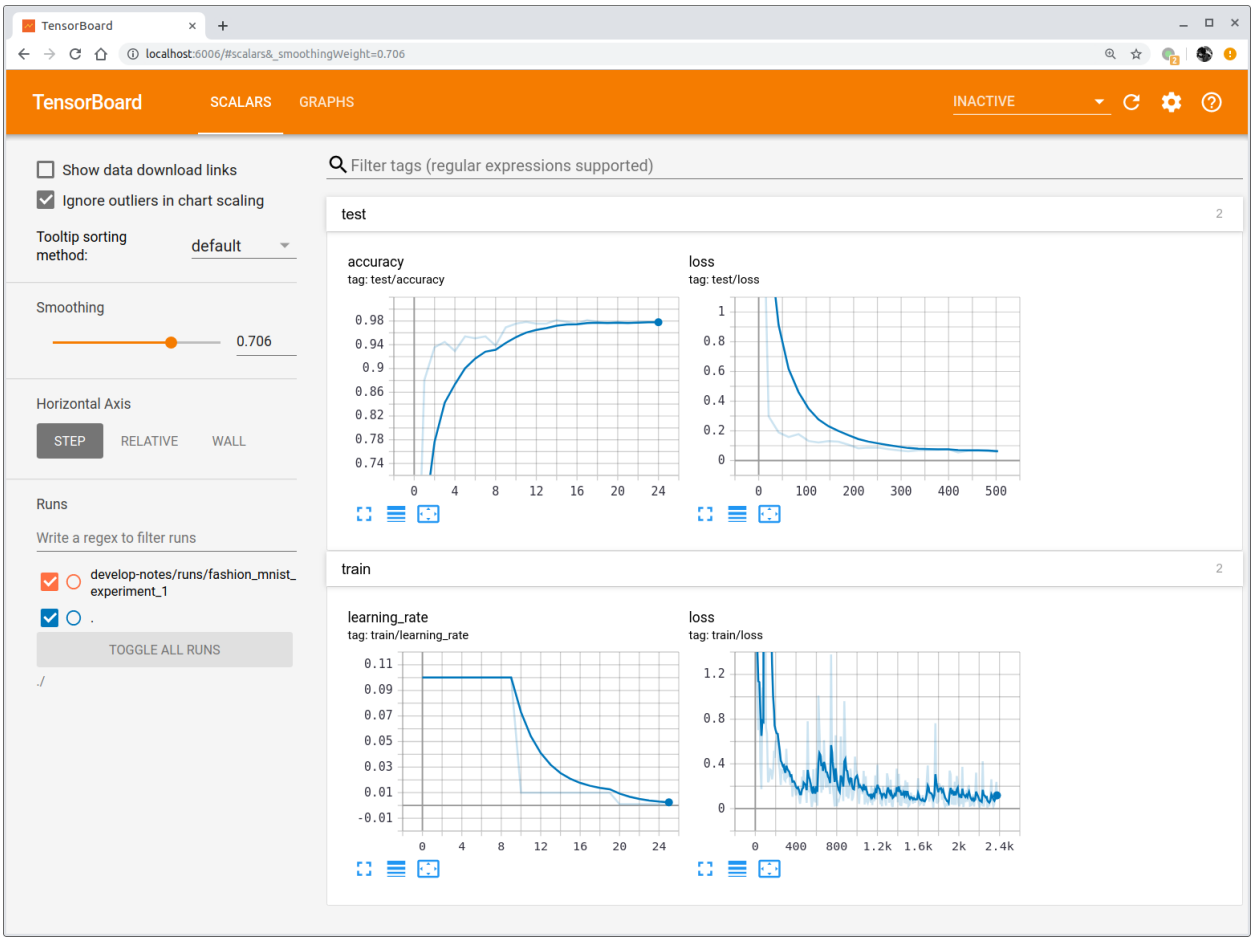
You can use the `scipts/train_cls.py` to train your classification model. Here is a train examples, for more parameter information, please use `python3 train_cls.py help` to view.

```
python3 train_cls.py --train-path ./classification/train \
                  --val-path ./tests/classification/val \
                  --model resnet18 \
                  --batch-size 16 \
                  --num-classes 4 \
                  --device cuda
```

It should start train and the console will print the training logs.

```
Train Epoch: 0 [0/1514 (0%)]    Loss: 1.878198
Train Epoch: 0 [160/1514 (11%)] Loss: 0.811605
Train Epoch: 0 [320/1514 (21%)] Loss: 0.774963
Train Epoch: 0 [480/1514 (32%)] Loss: 0.817051
Train Epoch: 0 [640/1514 (42%)] Loss: 0.869388
Train Epoch: 0 [800/1514 (53%)] Loss: 4.763704
Train Epoch: 0 [960/1514 (63%)] Loss: 0.968885
Train Epoch: 0 [1120/1514 (74%)] Loss: 4.856205
Train Epoch: 0 [1280/1514 (84%)] Loss: 1.343379
Train Epoch: 0 [1440/1514 (95%)] Loss: 0.551179

Test set: Average loss: 16.4018, Accuracy: 68/326 (21%)

Train Epoch: 1 [0/1514 (0%)]    Loss: 2.768502
Train Epoch: 1 [160/1514 (11%)] Loss: 0.424574
Train Epoch: 1 [320/1514 (21%)] Loss: 0.572497
Train Epoch: 1 [480/1514 (32%)] Loss: 1.539173
Train Epoch: 1 [640/1514 (42%)] Loss: 0.707925
Train Epoch: 1 [800/1514 (53%)] Loss: 0.545577
Train Epoch: 1 [960/1514 (63%)] Loss: 0.956915
Train Epoch: 1 [1120/1514 (74%)] Loss: 0.556552
Train Epoch: 1 [1280/1514 (84%)] Loss: 0.825140
Train Epoch: 1 [1440/1514 (95%)] Loss: 0.588212

Test set: Average loss: 0.4656, Accuracy: 254/326 (78%)

Train Epoch: 2 [0/1514 (0%)]    Loss: 0.422114
Train Epoch: 2 [160/1514 (11%)] Loss: 0.273431
Train Epoch: 2 [320/1514 (21%)] Loss: 0.505005
....
```

You can also open Tensorboard to view the loss and test accuracy during training.



And we provide lots of classification model, and all of them support multi-channel(>4) tiff image as input.

- VGG: `vgg11`, `vgg11_bn`, `vgg13`, `vgg13_bn`, `vgg16`, `vgg16_bn`, `vgg19_bn`, `vgg19`
- ResNet: `resnet18`, `resnet34`, `resnet50`, `resnet101`, `resnet152`, `resnext50_32x4d`,'`resnext101_32x8d`, `wide_resnet50_2`, `wide_resnet101_2`
- DenseNet: `densenet121`, `densenet169`, `densenet201`
- Inception: `inception_v3`
- MobileNet: `mobilenet_v2`
- EfficientNet: `efficientnet_b0`, `efficientnet_b1`, `efficientnet_b2`, `efficientnet_b3`,'`efficientnet_b4`, `efficientnet_b5`, `efficientnet_b6`, `efficientnet_b7`
- ResNeSt: `resnest50`, `resnest101`, `resnest200`, `resnest269`

3.3 Inference new image

[TODO]

CHAPTER 4

Semantic Segmentation

This tutorial will teach you how to use torchsat to train your semantic segmentation model for your satellite project.

4.1 Prepare training data

If your training data is a large image (such as 10000 x 10000 pixels), you can use torchsat command-line tool to crop it into small pictures for training. There are two cases:

1. If your sample labels are vectors, then you can use `ts make_mask_seg` to directly generate small samples that can be directly used for training.
2. If your sample label is a picture, then you can use `ts make_mask_cls` to cut the large satellite image and label image separately.

The final generated train data needs to be organized as follows:

```
.
├── train
│   ├── image
│   │   ├── train_1.jpg
│   │   ├── train_2.jpg
│   │   ├── ...
│   └── label
│       ├── train_1.png
│       ├── train_2.png
│       ├── ...
└── val
    ├── image
    │   ├── val_10.jpg
    │   ├── val_11.jpg
    │   ├── ...
    └── label
        ├── val_10.png
```

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```
            ├── val_11.png
            ├── ...
```

4.2 Training model

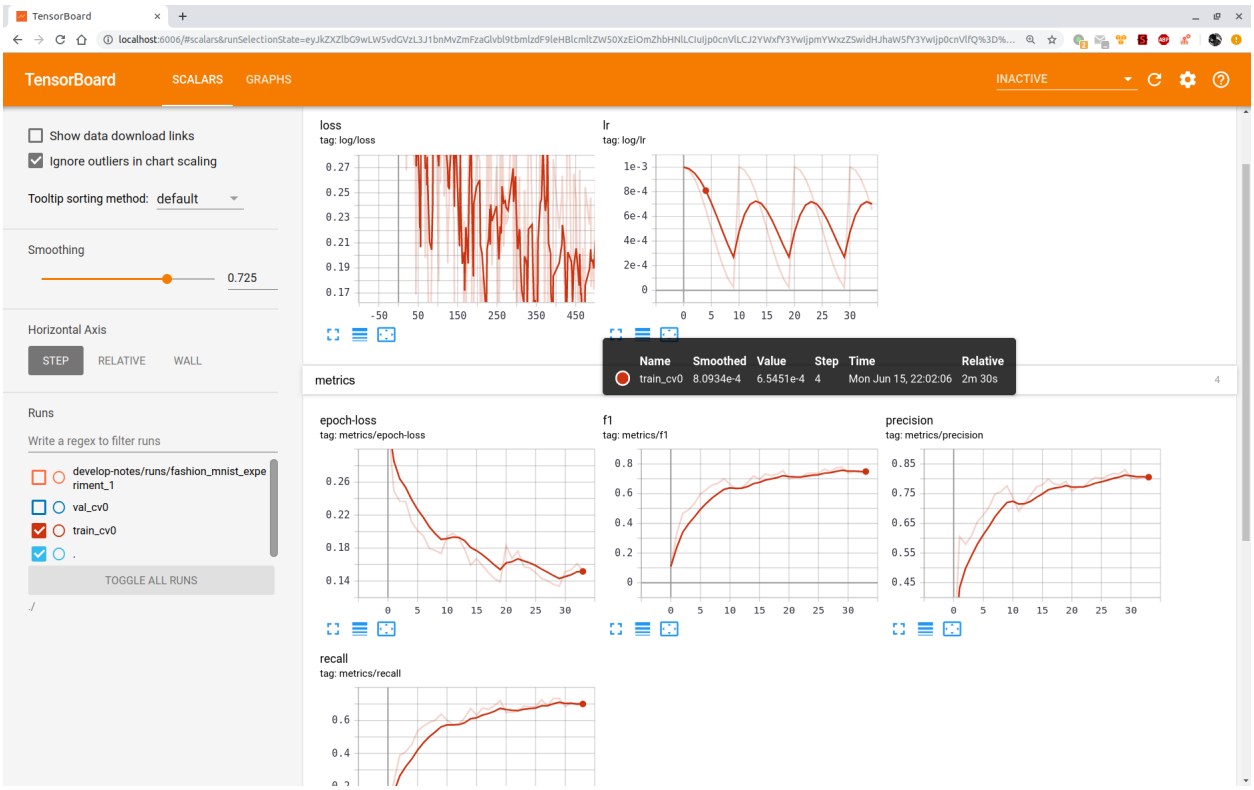
You can use scripts/train_seg.py to train your model. You can also modify some of them according to your own needs, such as `data augmentation`, `loss function`, `optimzer`, `model`.

```
usage: test.py [-h] [--train-path TRAIN_PATH] [--val-path VAL_PATH]
               [--extensions EXTENSIONS [EXTENSIONS ...]] [--model MODEL]
               [--pretrained PRETRAINED] [--resume PATH]
               [--num-classes NUM_CLASSES] [--in-channels IN_CHANNELS]
               [--device DEVICE] [-b BATCH_SIZE] [--epochs EPOCHS] [--lr LR]
               [--print-freq PRINT_FREQ] [--ckp-dir CKP_DIR]

TorchSat Segmentation Training Script

optional arguments:
  -h, --help            show this help message and exit
  --train-path TRAIN_PATH
                        train dataset path
  --val-path VAL_PATH   validate dataset path
  --extensions EXTENSIONS [EXTENSIONS ...]
                        the train image extension
  --model MODEL         model name. default, unet34
  --pretrained PRETRAINED
                        use ImageNet pretrained params
  --resume PATH         path to latest checkpoint (default: none)
  --num-classes NUM_CLASSES
                        num of classes
  --in-channels IN_CHANNELS
                        input image channels
  --device DEVICE       device
  -b BATCH_SIZE, --batch-size BATCH_SIZE
                        batch size
  --epochs EPOCHS       epochs
  --lr LR               initial learning rate
  --print-freq PRINT_FREQ
                        print frequency
  --ckp-dir CKP_DIR     path to save checkpoint
```

You can also open Tensorboard to view the loss and test accuracy during training.



Currently supported models are:

- UNet
  - ResNet Backbone: `unet_restnet18`, `unet_resnet34`, `unet_resnet101`

4.3 Inference new image

[TODO]

CHAPTER 5

Object Detection

[TODO]

CHAPTER 6

Change Detection

This is tutorial for satellite change detection.

6.1 Prepare the training data

The satellite change detection dataset should be organized by the following struct.

```
.
├── train
│   ├── pre
│   │   ├── train_1.png
│   │   ├── train_2.png
│   │   ├── ...
│   ├── post
│   │   ├── train_1.png
│   │   ├── train_2.png
│   │   ├── ...
│   └── label
│   │   ├── train_1.png
│   │   ├── train_2.png
│   │   ├── ...
└── val
    ├── pre
    │   ├── val_10.png
    │   ├── val_11.png
    │   ├── ...
    ├── post
    │   ├── val_10.png
    │   ├── val_11.png
    │   ├── ...
    └── label
        ├── val_10.png
```

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```
        ├── val_11.png
        ├── ...
```

You can use the `make_mask_cls` generate the pre and post image.

6.2 train a model

6.3 We provide the following models:

CHAPTER 7

Data Augumentation

This notebook show the data augmentation for classification, detection and segmentation.

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
from PIL import Image
import tifffile
from torchsat.transforms import transforms_cls, transforms_det, transforms_seg
from torchsat.utils.visualizer import plot_img, plot_bbox, plot_mask
```

7.1 Image classification

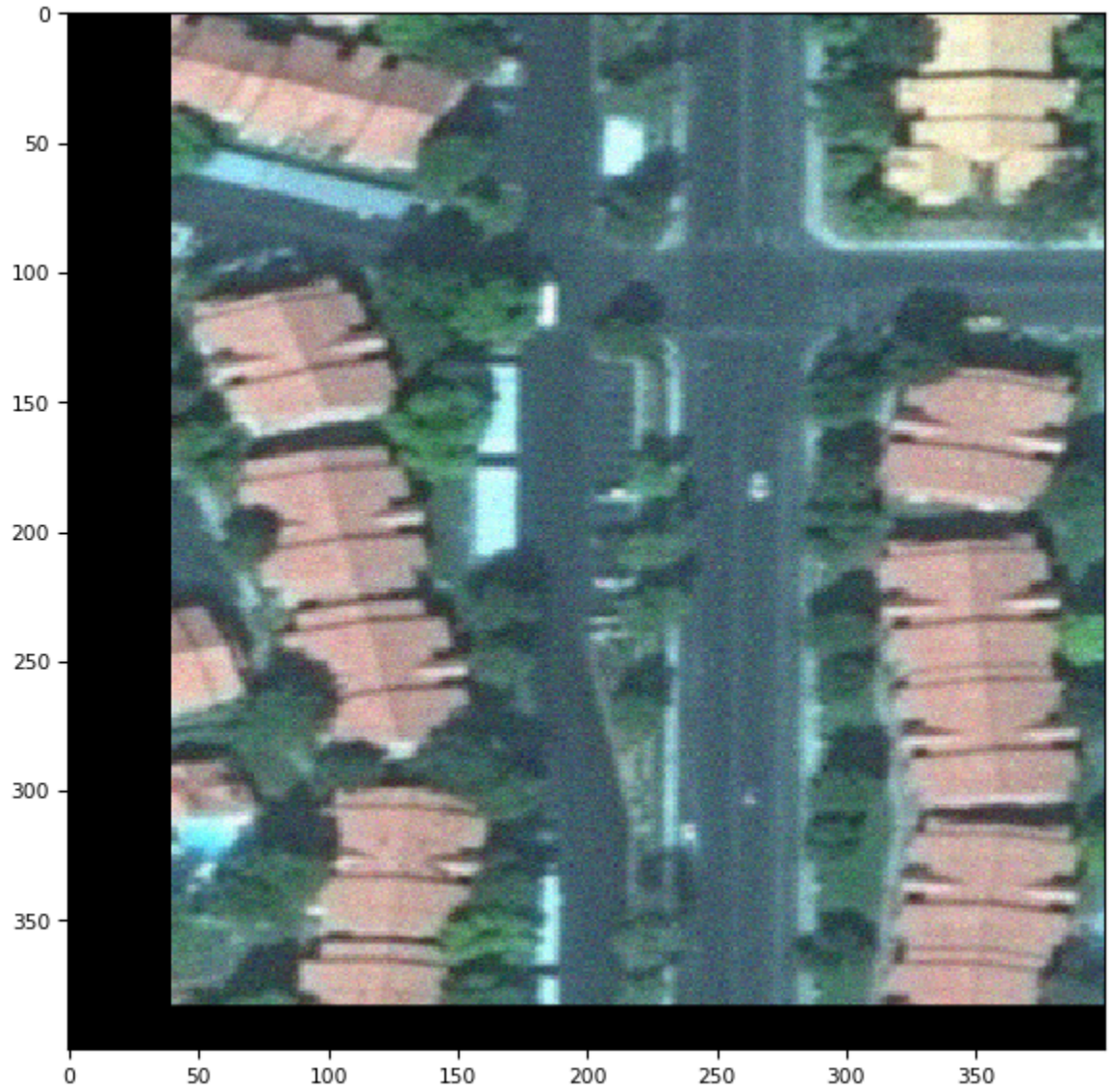
1. 3 channel image

```
fp = '../tests/fixtures/different-types/jpeg_3channel_uint8.jpeg'
img = np.array(Image.open(fp))
plot_img(img)
```

```
<Figure size 720x576 with 0 Axes>
```


```
# apply the classification transform
result = transforms_cls.Compose([
    transforms_cls.GaussianBlur(kernel_size=9),
    transforms_cls.RandomNoise(),
    transforms_cls.RandomHorizontalFlip(p=1),
    transforms_cls.RandomShift(max_percent=0.1),
    transforms_cls.Resize(400)
])(img)
plot_img(result)
```

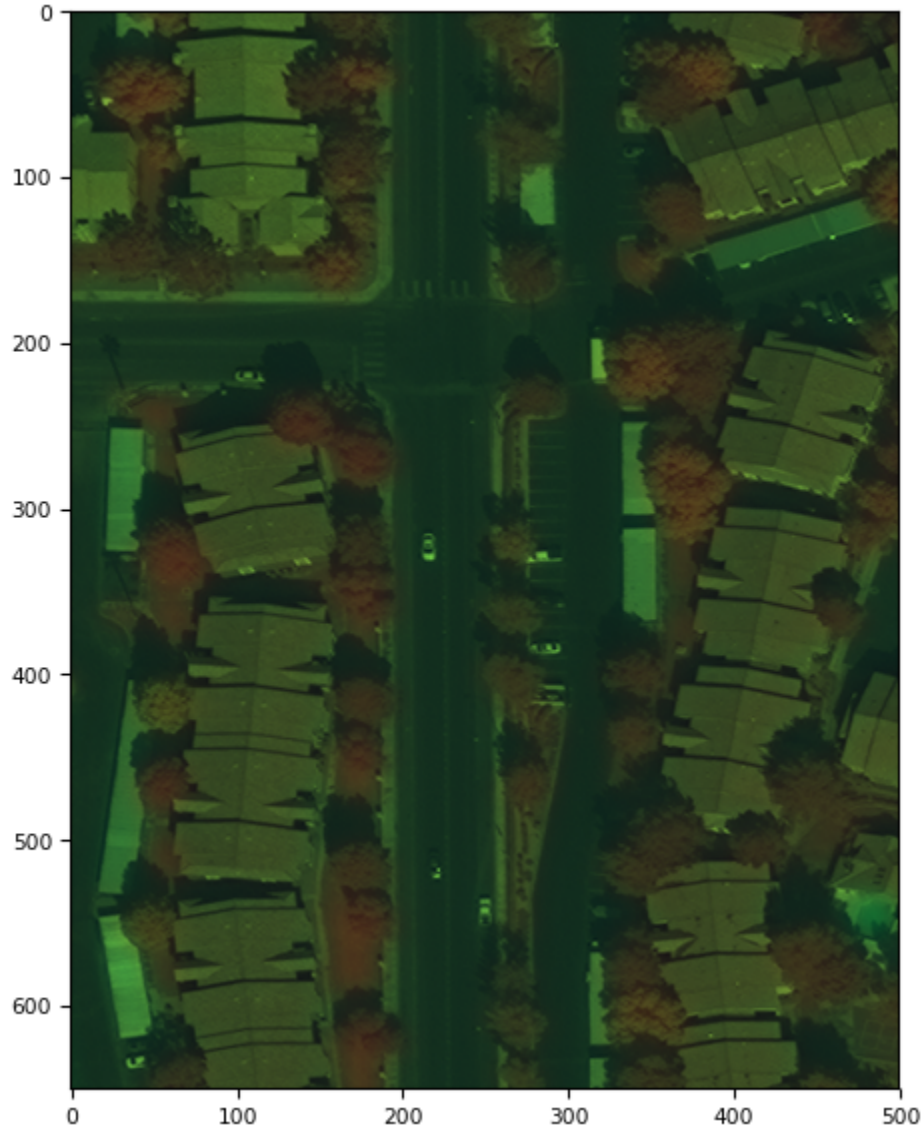
```
<Figure size 720x576 with 0 Axes>
```



2. 8 channel uint16 tiff image

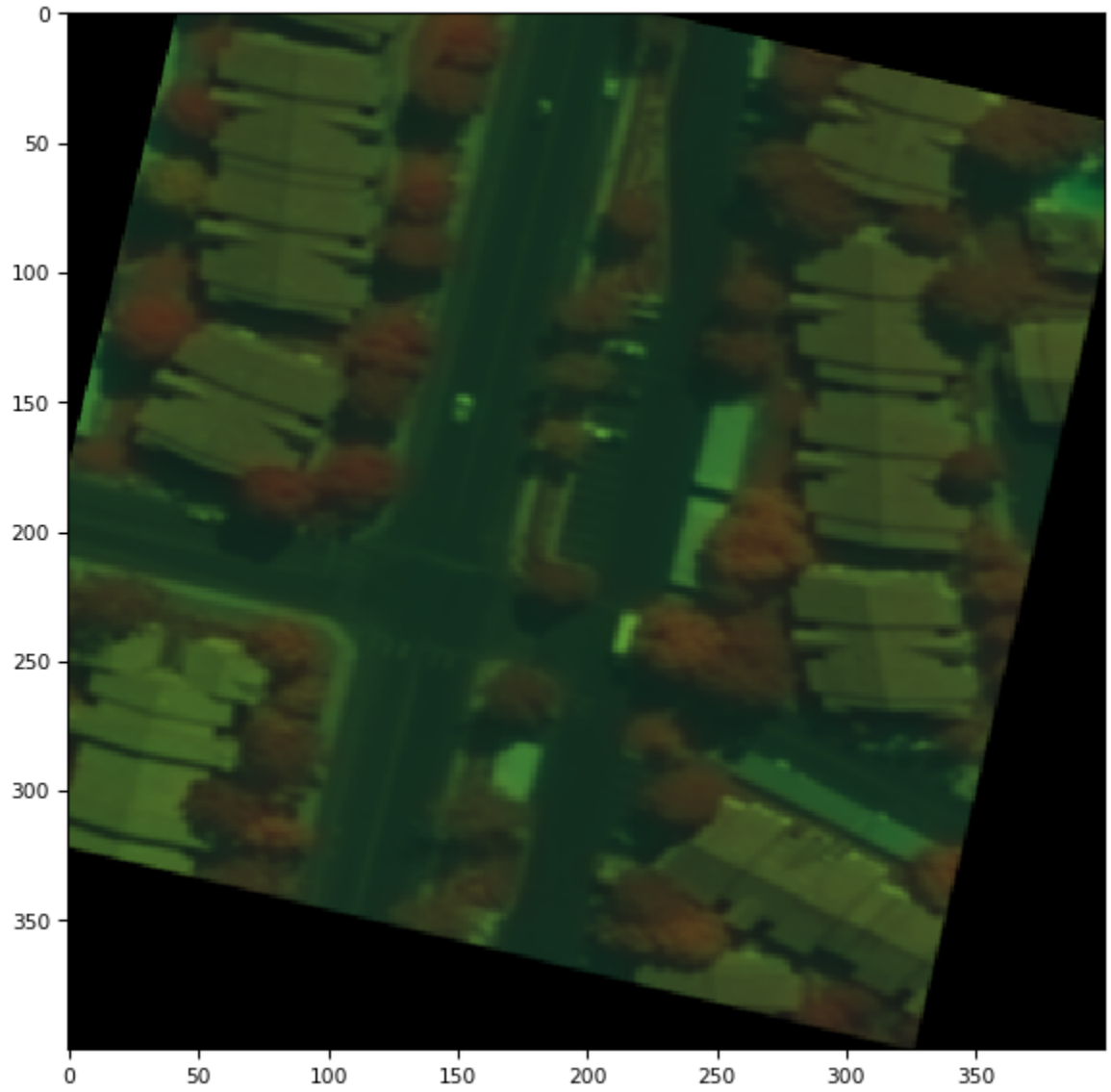
```
fp = '../tests/fixtures/different-types/tiff_8channel_uint16.tif'
img = tifffile.imread(fp)
print('image shsape: '.format(img.shape))
plot_img(img, channels=(8,3,1))
```

```
image shsape:



<Figure size 720x576 with 0 Axes>
```




```
# apply the classification transform
result = transforms_cls.Compose([
    transforms_cls.GaussianBlur(kernel_size=9),
    transforms_cls.RandomVerticalFlip(p=1),
    transforms_cls.RandomShift(max_percent=0.1),
    transforms_cls.Resize(400),
    transforms_cls.RandomRotation(30),
#     transforms_cls.ElasticTransform()
])(img)
plot_img(result, channels=(8,3,1))
```

```
<Figure size 720x576 with 0 Axes>
```



7.2 Object detection

```
fp_img = '../tests/fixtures/different-types/jpeg_3channel_uint8.jpeg'
img = np.array(Image.open(fp_img))
bboxes = np.array([
    [210, 314, 225, 335],
    [273, 324, 299, 337],
    [275, 378, 302, 391],
    [213, 506, 228, 527],
    [241, 534, 257, 556],
    [31, 627, 49, 640],
    [99, 213, 120, 229],
    [61, 1, 164, 155],
    [1, 59, 44, 138],
    [61, 249, 165, 342],
```

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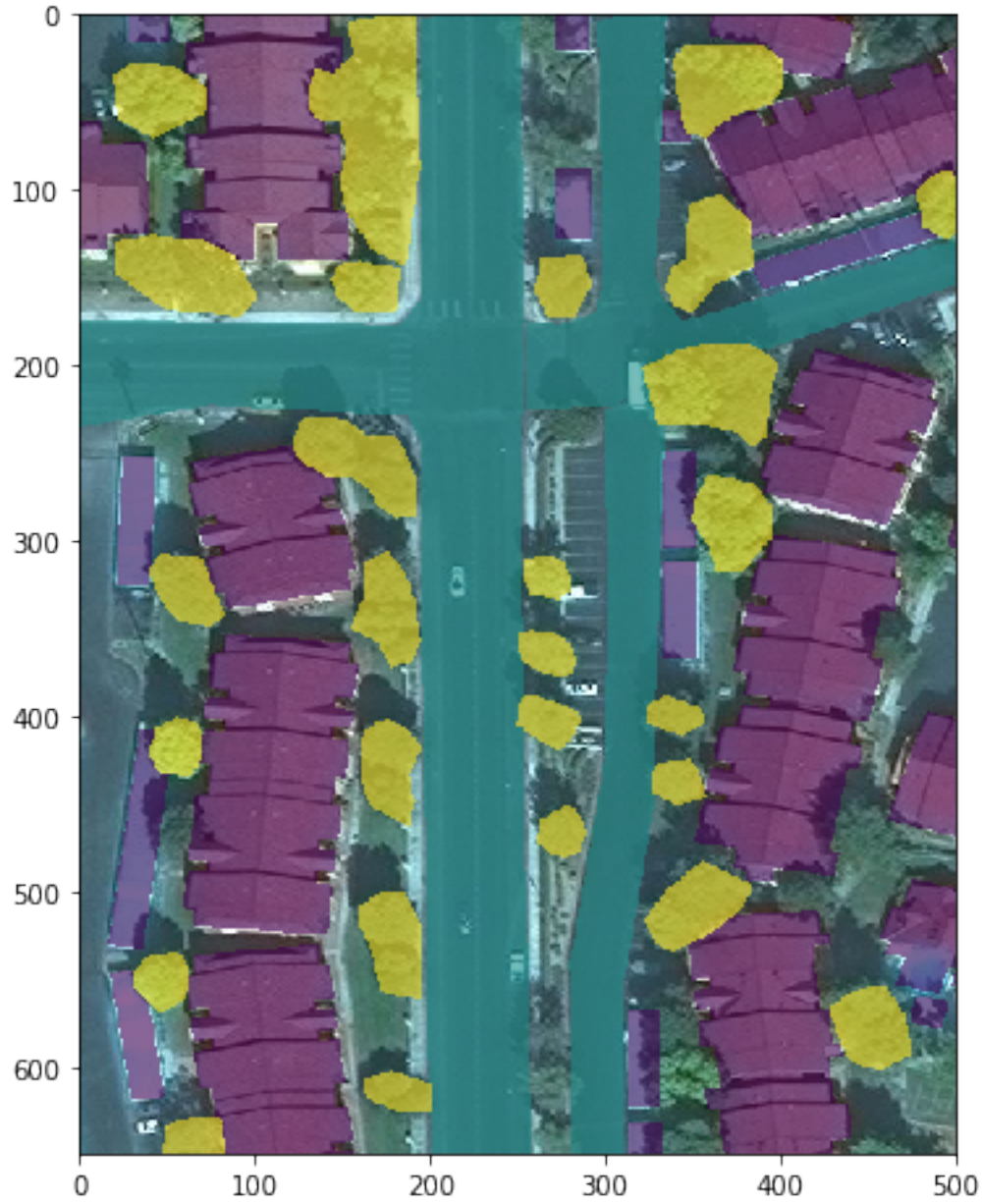
```
    [61, 352, 159, 526],
    [58, 535, 163, 650],
    [360, 1, 444, 41],
    [354, 19, 500, 124],
    [388, 190, 491, 292],
    [374, 298, 471, 398],
    [352, 398, 448, 500],
    [457, 399, 500, 471],
    [457, 494, 500, 535],
    [344, 512, 439, 650],
    [455, 532, 500, 574],
])
labels = [1,1,1,1,1,1,1,2,2,2,2,2,2,2,2,2,2,2,2,2,3]
classes = ['car', 'building', 'pool']
plot_bbox(img, bboxes, labels=labels, classes=classes)
```

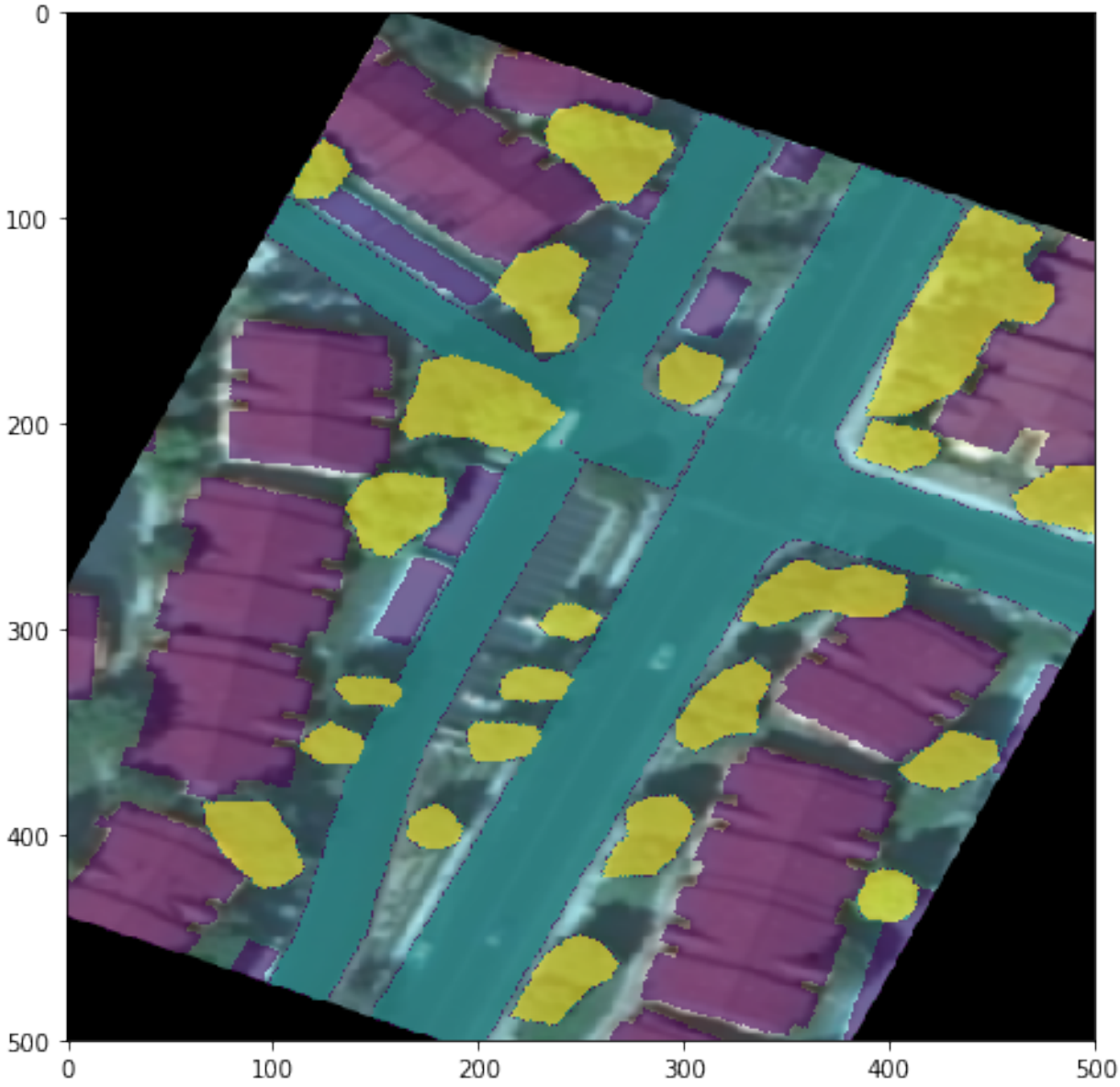

```
# apply the object detection transform
result_img, result_bboxes, result_labels = transforms_det.Compose([
    transforms_det.GaussianBlur(kernel_size=3),
    transforms_det.RandomFlip(p=1),
])(img, bboxes, labels)
plot_bbox(result_img, result_bboxes, labels=result_labels, classes=classes)
```

7.3 Semantic segmentation

```
fp_img = '../tests/fixtures/different-types/jpeg_3channel_uint8.jpeg'
fp_mask = '../tests/fixtures/masks/mask_tiff_3channel_uint8.png'
img = np.array(Image.open(fp_img))
mask = np.array(Image.open(fp_mask))
plot_mask(img, mask)
```




```
# apply the classification transform
result_img, result_mask = transforms_seg.Compose([
    transforms_seg.GaussianBlur(kernel_size=9),
    transforms_seg.RandomVerticalFlip(p=1),
    transforms_seg.RandomShift(max_percent=0.1),
    transforms_seg.RandomRotation(30),
    transforms_seg.Resize((500,500)),
#     transforms_seg.ElasticTransform()
])(img, mask)
plot_mask(result_img, result_mask)
```


0
100
200
300
400
500
0
100
200
300
400
500

CHAPTER 8

Useful Tools

Collections of usefle tools for satellite deep learning processing.

8.1 processing tools

8.1.1 make_mask_cls

This tool can split the large satellite image(e.g.,10000 x 10000 pixel) to small chips(e.g., 512 x 512 pixel). Both the satellite image and label image can use this tool.

```
Usage: ts make_mask_cls [OPTIONS]

  this tool is to patch the large satellite image to small image.

Options:
  --filepath TEXT      the target satellite image to split. Note: the file
                       should have crs
  --width INTEGER      the width of the patched image, default 512
  --height INTEGER     the height of the patched image, default 512
  --drop_last BOOLEAN  set to True to drop the last column and row, if the
                       image size is not divisible by the height and width.
                       default True.
  --outpath TEXT       the output file path
  --colormap BOOLEAN   weather write the colormap to the output patched image.
                       only work for single channel image. default False.
  --extensions TEXT    the train image extension, only work for dirctory file
                       path.
  --help               Show this message and exit.
```

example:

```
ts make_mask_cls --filepath ./tests/classification \
                 --width 512 \
                 --height 512 \
                 --drop_last True \
                 --extensions tif \
                 --extensions tiff \
                 --outpath ./test/out
```

8.1.2 make_mask_seg

This tool is to patch the large satellite image to small image and label for segmentation. The input should be projected satellite image and vector file. e.g., geojson shpfile.

```
Usage: ts make_mask_seg [OPTIONS]

  this tool is to patch the large satellite image to small image and label
  for segmentation.

Options:
  --image_file TEXT    the target satellite image to split. Note: the file
                       should have crs
  --label_file TEXT    the corresponding label file of the satellite image.
                       vector or raster file. Note the crs should be same as
                       satellite image.
  --field TEXT         field to burn
  --width INTEGER      the width of the patched image
  --height INTEGER     the height of the patched image
  --drop_last BOOLEAN  set to True to drop the last column and row, if the
                       image size is not divisible by the height and width.
  --outpath TEXT       the output file path
  --help               Show this message and exit.
```

8.1.3 calcuate_mean_std

This tool is for calcuating each channel mean and std value of the datasets.

```
Usage: ts calcuate_mean_std [OPTIONS]

  calcuate the datasets mean and std value

Options:
  --root PATH         root dir of image datasets  [required]
  --percent FLOAT     percent of images to calcuate
  --channels INTEGER  datasets image channels
  --maxvalue FLOAT    max value of all images default: {255}
  --extension TEXT    file suffix to calcuate, default ('jpg', 'jpeg', 'png',
                      'tif', 'tiff')
  --help              Show this message and exit.
```

example:

```
ts calcuate_mean_std --root /tests/classification/val/
100%|| 163/163 [00:02<00:00, 70.53it/s]
scaled  mean:[0.36473823 0.40924644 0.41250621]
```

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```
scaled  std: [0.09052812 0.07698209 0.0671676 ]
orginal mean: [ 93.00824798 104.35784201 105.18908467]
orginal std: [23.08467009 19.6304323  17.12773828]
```

8.2 train scripts

The script can be used for training the model. You can modify the script according to your own project. It is independent of torchsat, you can get it from the `scripts` directory from torchsat repo.

8.2.1 scripts/train_cls.py

```
usage: scripts/train_cls.py [-h] [--train-path TRAIN_PATH] [--val-path VAL_PATH]
               [--model MODEL] [--pretrained PRETRAINED] [--resume PATH]
               [--num-classes NUM_CLASSES] [--in-channels IN_CHANNELS]
               [--device DEVICE] [-b BATCH_SIZE] [--epochs EPOCHS] [--lr LR]
               [--print-freq PRINT_FREQ] [--ckp-dir CKP_DIR]

TorchSat Classification Training

optional arguments:
  -h, --help            show this help message and exit
  --train-path TRAIN_PATH
                        train dataset path
  --val-path VAL_PATH   validate dataset path
  --model MODEL         the classification model
  --pretrained PRETRAINED
                        use the ImageNet pretrained model or not
  --resume PATH         path to latest checkpoint (default: none)
  --num-classes NUM_CLASSES
                        num of classes
  --in-channels IN_CHANNELS
                        input image channels
  --device DEVICE
  -b BATCH_SIZE, --batch-size BATCH_SIZE
                        batch size
  --epochs EPOCHS       train epochs
  --lr LR               initial learning rate
  --print-freq PRINT_FREQ
                        print frequency
  --ckp-dir CKP_DIR     path to save checkpoint
```

CHAPTER 9

API Reference

9.1 torchsat package

9.1.1 Subpackages

torchsat.datasets package

Submodules

torchsat.datasets.eurosat module

class torchsat.datasets.eurosat.**EuroSAT**(*root*, *mode='RGB'*, *download=False*, ***kwargs*)

Bases: *torchsat.datasets.folder.DatasetFolder*

download()

url_allband = 'http://madm.dfki.de/files/sentinel/EuroSATallBands.zip'

url_rgb = 'http://madm.dfki.de/files/sentinel/EuroSAT.zip'

torchsat.datasets.folder module

class torchsat.datasets.folder.**ChangeDetectionDataset**(*root*, *extentions='jpg'*, *transforms=None*)

Bases: torch.utils.data.dataset.Dataset

A generic data loader where the images are arranged in this way: ::

.

├── train │ ├── pre │ │ ├── train_1.png │ │ ├── train_2.png │ │ ├── ... │ ├── post │ │ ├── train_1.png │ │ ├── train_2.png │ │ ├── ... │ └── label │ ├── train_1.png │ ├── train_2.png │ ├── ... └── val

├── pre │ ├── val_10.png │ ├── val_11.png │ ├── ... ├── post │ ├── val_10.png │ ├── val_11.png │ ├── ... └── label

├── val_10.png ├── val_11.png ├── ...

Args: root (string): root dir of train or validate dataset. extensions (tuple or list): extention of training image.

class torchsat.datasets.folder.**DatasetFolder**(*root*, *loader*, *extensions*, *classes=None*, *class_to_idx=None*, *transform=None*, *target_transform=None*)

Bases: torch.utils.data.dataset.Dataset

A generic data loader where the samples are arranged in this way:

```
root/class_x/xxx.ext
root/class_x/xxy.ext
root/class_x/xxz.ext

root/class_y/123.ext
root/class_y/nsdf3.ext
root/class_y/asd932_.ext
```

Args:

root (string): Root directory path. loader (callable): A function to load a sample given its path. extensions (list[string]): A list of allowed extensions. classes (callable, optional): List of the class names. class_to_idx (callable, optional): Dict with items (class_name, class_index). transform (callable, optional): A function/transform that takes in

a sample and returns a transformed version. E.g, transforms.RandomCrop for images.

target_transform (callable, optional): A function/transform that takes in the target and transforms it.

Attributes: classes (list): List of the class names. class_to_idx (dict): Dict with items (class_name, class_index). samples (list): List of (sample path, class_index) tuples targets (list): The class_index value for each image in the dataset

class torchsat.datasets.folder.**ImageFolder**(*root*, *transform=None*, *target_transform=None*, *loader=<function default_loader>*, ***kwargs*)

Bases: *torchsat.datasets.folder.DatasetFolder*

A generic data loader where the images are arranged in this way:

```
root/dog/xxx.png
root/dog/xxy.png
root/dog/xxz.png

root/cat/123.png
root/cat/nsdf3.png
root/cat/asd932_.png
```

Args:

root (string): Root directory path. transform (callable, optional): A function/transform that takes in an PIL image

and returns a transformed version. E.g, `transforms.RandomCrop`

target_transform (callable, optional): A function/transform that takes in the target and transforms it.

loader (callable, optional): A function to load an image given its path.

Attributes: classes (list): List of the class names. class_to_idx (dict): Dict with items (class_name, class_index). imgs (list): List of (image path, class_index) tuples

class torchsat.datasets.folder.**SegmentationDataset**(*root*, *extentions='jpg'*, *transforms=None*)

Bases: `object`

A generic data loader where the images are arranged in this way: :: . ├── train │ ├── image │ │ ├── train_1.png │ │ ├── train_2.png │ │ ├── ... │ └── label │ ├── train_1.png │ ├── train_2.png │ ├── ... └── val

├── image │ ├── val_10.png │ ├── val_11.png │ ├── ... └── label

├── val_10.png ├── val_11.png ├── ...

Args: root (string): root dir of train or validate dataset. extensions (tuple or list): extention of training image.

torchsat.datasets.folder.**has_file_allowed_extension**(*filename*, *extensions*)

Checks if a file is an allowed extension.

Args: filename (string): path to a file extensions (iterable of strings): extensions to consider (lowercase)

Returns: bool: True if the filename ends with one of given extensions

torchsat.datasets.folder.**is_image_file**(*filename*)

Checks if a file is an allowed image extension.

Args: filename (string): path to a file

Returns: bool: True if the filename ends with a known image extension

torchsat.datasets.folder.**make_dataset**(*dir*, *class_to_idx*, *extensions*)

torchsat.datasets.nwpu_resisc45 module

class torchsat.datasets.nwpu_resisc45.**NWPU_RESISC45**(*root*, *download=False*, ***kwargs*)

Bases: *torchsat.datasets.folder.DatasetFolder*

download()

url = 'https://sov8mq.dm.files.1drv.com/y4m_Fo6ujI52LiWHDzaRZVtkMIZxF7aqjX2q7KdVr329zV

torchsat.datasets.patternnet module

class torchsat.datasets.patternnet.**PatternNet**(*root*, *download=False*, ***kwargs*)

Bases: *torchsat.datasets.folder.DatasetFolder*

download()

url = 'https://doc-0k-9c-docs.googleusercontent.com/docs/securesc/s4mst7k8sdlkn5gslv2v

torchsat.datasets.sat module

class torchsat.datasets.sat.**SAT**(*root*, *mode='SAT-4'*, *image_set='train'*, *download=False*, *transform=False*, *target_transform=False*)

Bases: torch.utils.data.dataset.Dataset

SAT-4 and SAT-6 datasets

Arguments: data {root} – [description]

Raises: ValueError – [description] ValueError – [description]

Returns: [type] – [description]

classes_sat4 = {'barren land': 0, 'grassland': 2, 'none': 3, 'trees': 1}

classes_sat6 = {'barren land': 1, 'building': 0, 'grassland': 3, 'road': 4, 'trees

download()

torchsat.datasets.utils module

torchsat.datasets.utils.**accimage_loader**(*path*)

torchsat.datasets.utils.**default_loader**(*path*)

torchsat.datasets.utils.**download_url**(*url*, *root*, *filename=None*, *md5=None*)

Download a file from a url and place it in root. Args:

url (str): URL to download file from root (str): Directory to place downloaded file in filename (str, optional): Name to save the file under. If None, use the basename of the URL md5 (str, optional): MD5 checksum of the download. If None, do not check

torchsat.datasets.utils.**gen_bar_updater**()

torchsat.datasets.utils.**image_loader**(*path*)

torchsat.datasets.utils.**pil_loader**(*path*)

torchsat.datasets.utils.**tifffile_loader**(*path*)

Module contents

torchsat.models package

Subpackages

torchsat.models.classification package

Submodules

torchsat.models.classification.densenet module

class torchsat.models.classification.densenet.**DenseNet**(*growth_rate=32*, *block_config=(6, 12, 24, 16)*, *num_init_features=64*, *bn_size=4*, *drop_rate=0*, *num_classes=1000*, *in_channels=3*, *memory_efficient=False*)

Bases: torch.nn.modules.module.Module

Densenet-BC model class, based on "Densely Connected Convolutional Networks" Args:

growth_rate (int) - how many filters to add each layer (*k* in paper) block_config (list of 4 ints) - how many layers in each pooling block num_init_features (int) - the number of filters to learn in the first convolution layer bn_size (int) - multiplicative factor for number of bottle neck layers

(i.e. bn_size * k features in the bottleneck layer)

drop_rate (float) - dropout rate after each dense layer num_classes (int) - number of classification classes memory_efficient (bool) - If True, uses checkpointing. Much more memory efficient,

but slower. Default: *False*. See "paper"

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the Module instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

torchsat.models.classification.densenet.**densenet121**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Densenet-121 model from "Densely Connected Convolutional Networks" Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr memory_efficient (bool) - If True, uses checkpointing. Much more memory efficient,

but slower. Default: *False*. See "paper"

torchsat.models.classification.densenet.**densenet169**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Densenet-169 model from "Densely Connected Convolutional Networks" Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr memory_efficient (bool) - If True, uses checkpointing. Much more memory efficient,

but slower. Default: *False*. See "paper"

torchsat.models.classification.densenet.**densenet201**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Densenet-201 model from "Densely Connected Convolutional Networks" Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr memory_efficient (bool) - If True, uses checkpointing. Much more memory efficient,

but slower. Default: *False*. See "paper"

torchsat.models.classification.densenet.**densenet161**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Densenet-161 model from "Densely Connected Convolutional Networks" Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr memory_efficient (bool) - If True, uses checkpointing. Much more memory efficient,

but slower. Default: *False*. See "paper"

torchsat.models.classification.inception module

class torchsat.models.classification.inception.**Inception3**(*num_classes=1000*, *in_channels=3*, *aux_logits=True*, *transform_input=False*)

Bases: torch.nn.modules.module.Module

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the Module instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

torchsat.models.classification.inception.**inception_v3**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Inception v3 model architecture from "Rethinking the Inception Architecture for Computer Vision". .. note:

```
**Important**: In contrast to the other models the inception_v3 expects tensors␣
↪with a size of
N x 3 x 299 x 299, so ensure your images are sized accordingly.
```

Args: pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr aux_logits (bool): If True, add an auxiliary branch that can improve training.

Default: *True*

transform_input (bool): If True, preprocesses the input according to the method with which it was trained on ImageNet. Default: *False*

torchsat.models.classification.mobilenet module

class torchsat.models.classification.mobilenet.**MobileNetV2**(*num_classes=1000*, *in_channels=3*, *width_mult=1.0*, *inverted_residual_setting=None*, *round_nearest=8*)

Bases: torch.nn.modules.module.Module

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the Module instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

torchsat.models.classification.mobilenet.**mobilenet_v2**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Constructs a MobileNetV2 architecture from "MobileNetV2: Inverted Residuals and Linear Bottlenecks". Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet module

class torchsat.models.classification.resnet.**ResNet**(*block*, *layers*, *num_classes=1000*, *in_channels=3*, *zero_init_residual=False*, *groups=1*, *width_per_group=64*, *replace_stride_with_dilation=None*, *norm_layer=None*)

Bases: torch.nn.modules.module.Module

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the Module instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

torchsat.models.classification.resnet.**resnet18**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNet-18 model from ‘”Deep Residual Learning for Image Recognition” <https://arxiv.org/pdf/1512.03385.pdf>’_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet. If in_channels is greater than 3, it will copy the parameters of imagenet to fill in order.

progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**resnet34**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNet-34 model from ‘”Deep Residual Learning for Image Recognition” <https://arxiv.org/pdf/1512.03385.pdf>’_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**resnet50**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNet-50 model from ‘”Deep Residual Learning for Image Recognition” <https://arxiv.org/pdf/1512.03385.pdf>’_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**resnet101**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNet-101 model from ‘”Deep Residual Learning for Image Recognition” <https://arxiv.org/pdf/1512.03385.pdf>’_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**resnet152**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNet-152 model from ‘”Deep Residual Learning for Image Recognition” <https://arxiv.org/pdf/1512.03385.pdf>’_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**resnext50_32x4d**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNeXt-50 32x4d model from “Aggregated Residual Transformation for Deep Neural Networks” Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**resnext101_32x8d**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

ResNeXt-101 32x8d model from “Aggregated Residual Transformation for Deep Neural Networks” Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**wide_resnet50_2**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Wide ResNet-50-2 model from “Wide Residual Networks” The model is the same as ResNet except for the bottleneck number of channels which is twice larger in every block. The number of channels in outer 1x1 convolutions is the same, e.g. last block in ResNet-50 has 2048-512-2048 channels, and in Wide ResNet-50-2 has 2048-1024-2048. Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.resnet.**wide_resnet101_2**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

Wide ResNet-101-2 model from "Wide Residual Networks" The model is the same as ResNet except for the bottleneck number of channels which is twice larger in every block. The number of channels in outer 1x1 convolutions is the same, e.g. last block in ResNet-50 has 2048-512-2048 channels, and in Wide ResNet-50-2 has 2048-1024-2048. Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg module

class torchsat.models.classification.vgg.**VGG**(*features*, *num_classes=1000*, *init_weights=True*)

Bases: torch.nn.modules.module.Module

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the Module instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

torchsat.models.classification.vgg.**vgg11**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 11-layer model (configuration "A") from '"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg11_bn**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 11-layer model (configuration "A") with batch normalization '"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg13**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 13-layer model (configuration "B") '"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg13_bn**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 13-layer model (configuration "B") with batch normalization '"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg16**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 16-layer model (configuration "D") ‘"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg16_bn**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 16-layer model (configuration "D") with batch normalization ‘"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg19_bn**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 19-layer model (configuration ‘E’) with batch normalization ‘"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

torchsat.models.classification.vgg.**vgg19**(*num_classes*, *in_channels=3*, *pretrained=False*, *progress=True*, ***kwargs*)

VGG 19-layer model (configuration "E") ‘"Very Deep Convolutional Networks For Large-Scale Image Recognition" <https://arxiv.org/pdf/1409.1556.pdf>'_ Args:

pretrained (bool): If True, returns a model pre-trained on ImageNet progress (bool): If True, displays a progress bar of the download to stderr

Module contents

torchsat.models.detection package

Submodules

torchsat.models.detection.ssd module

Module contents

torchsat.models.segmentation package

Submodules

torchsat.models.segmentation.pspnet module

class torchsat.models.segmentation.pspnet.**PSPNet**(*num_classes*, *in_channels=3*, *backbone='resnet50'*, *pretrained=True*, *use_aux=True*)

Bases: torch.nn.modules.module.Module

PSPNet, currently only support 3 channels.

Args: nn ([type]): [description]

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

freeze_bn()

get_backbone_params()

get_decoder_params()

torchsat.models.segmentation.unet module

class torchsat.models.segmentation.unet.**UNetResNet**(*encoder_depth*, *num_classes*, *in_channels=3*, *num_filters=32*, *dropout_2d=0.0*, *pretrained=False*, *is_deconv=False*)

Bases: `torch.nn.modules.module.Module`

PyTorch U-Net model using ResNet(34, 101 or 152) encoder. UNet: https://arxiv.org/abs/1505.04597 ResNet: https://arxiv.org/abs/1512.03385 Proposed by Alexander Buslaev: https://www.linkedin.com/in/al-buslaev/

Args: encoder_depth (int): Depth of a ResNet encoder (34, 101 or 152). num_classes (int): Number of output classes. num_filters (int, optional): Number of filters in the last layer of decoder. Defaults to 32. dropout_2d (float, optional): Probability factor of dropout layer before output layer. Defaults to 0.2. pretrained (bool, optional):

False - no pre-trained weights are being used. True - ResNet encoder is pre-trained on ImageNet. Defaults to False.

is_deconv (bool, optional): False: bilinear interpolation is used in decoder. True: deconvolution is used in decoder. Defaults to False.

Raises: ValueError: [description] NotImplementedError: [description]

Returns: [type]: [description]

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

torchsat.models.segmentation.unet.**unet_resnet34**(*num_classes*, *in_channels=3*, *pretrained=False*, ***kwargs*)

torchsat.models.segmentation.unet.**unet_resnet101**(*num_classes*, *in_channels=3*, *pretrained=False*, ***kwargs*)

torchsat.models.segmentation.unet.**unet_resnet152**(*num_classes*, *in_channels=3*, *pretrained=False*, ***kwargs*)

Module contents

Submodules

torchsat.models.utils module

torchsat.models.utils.**get_model**(*name: str*, *num_classes: int*, ***kwargs*)

Module contents

torchsat.transforms package

Submodules

torchsat.transforms.functional module

torchsat.transforms.functional.**adjust_brightness**(*img*, *value=0*)

torchsat.transforms.functional.**adjust_contrast**(*img*, *factor*)

torchsat.transforms.functional.**adjust_hue**()

torchsat.transforms.functional.**adjust_saturation**()

torchsat.transforms.functional.**bbox_crop**(*bboxes*, *top*, *left*, *height*, *width*)
crop bbox

Arguments: img {ndarray} – image to be croped top {int} – top size left {int} – left size height {int} – croped height width {int} – croped width

torchsat.transforms.functional.**bbox_hflip**(*bboxes*, *img_width*)

horizontal flip the bboxes ^

.....

^

Args: bbox (ndarray): bbox ndarray [box_nums, 4] flip_code (int, optional): [description]. Defaults to 0.

torchsat.transforms.functional.**bbox_pad**(*bboxes*, *padding*)

torchsat.transforms.functional.**bbox_resize**(*bboxes*, *img_size*, *target_size*)
resize the bbox

Args: bboxes (ndarray): bbox ndarray [box_nums, 4] img_size (tuple): the image height and width target_size (int, or tuple): the target bbox size.

Int or Tuple, if tuple the shape should be (height, width)

torchsat.transforms.functional.**bbox_shift**(*bboxes*, *top*, *left*)
shift the bbox

Arguments: bboxes {ndarray} – input bboxes, should be num x 4 top {int} – shit to top value, positive mean move down, negative mean move up. left {int} – shit to left value, positive mean move right, negative mean move left.

Returns: [ndarray] – shifted bboxes

torchsat.transforms.functional.**bbox_vflip**(*bboxes*, *img_height*)

vertical flip the bboxes . . . .

>.....< . . . . Args:

bbox (ndarray): bbox ndarray [box_nums, 4] flip_code (int, optional): [description]. Defaults to 0.

torchsat.transforms.functional.**center_crop**(*img*, *output_size*)
crop image

Arguments: img {ndarray} – input image output_size {number or sequence} – the output image size. if sequence, should be [h, w]

Raises: ValueError – the input image is large than original image.

Returns: ndarray image – return croped ndarray image.

torchsat.transforms.functional.**crop**(*img*, *top*, *left*, *height*, *width*)
crop image

Arguments: img {ndarray} – image to be croped top {int} – top size left {int} – left size height {int} – croped height width {int} – croped width

torchsat.transforms.functional.**elastic_transform**(*image*, *alpha*, *sigma*, *alpha_affine*, *interpolation=1*, *border_mode=4*, *random_state=None*, *approximate=False*)
Elastic deformation of images as described in [Simard2003] (with modifications). Based on https://gist.github.com/erniejunior/601cdf56d2b424757de5 .. [Simard2003] Simard, Steinkraus and Platt, "Best Practices for

Convolutional Neural Networks applied to Visual Document Analysis", in Proc. of the International Conference on Document Analysis and Recognition, 2003.

torchsat.transforms.functional.**flip**(*img*, *flip_code*)

torchsat.transforms.functional.**gaussian_blur**(*img*, *kernel_size*)

torchsat.transforms.functional.**hflip**(*img*)

torchsat.transforms.functional.**noise**(*img*, *mode='gaussain'*, *percent=0.02*)
TODO: Not good for uint16 data

torchsat.transforms.functional.**normalize**(*tensor*, *mean*, *std*, *inplace=False*)
Normalize a tensor image with mean and standard deviation.

Note: This transform acts out of place by default, i.e., it does not mutates the input tensor.

See `Normalize` for more details.

Args: tensor (Tensor): Tensor image of size (C, H, W) to be normalized. mean (sequence): Sequence of means for each channel. std (sequence): Sequence of standard deviations for each channel.

Returns: Tensor: Normalized Tensor image.

torchsat.transforms.functional.**pad**(*img*, *padding*, *fill=0*, *padding_mode='constant'*)

torchsat.transforms.functional.**preserve_channel_dim**(*func*)
Preserve dummy channel dim.

torchsat.transforms.functional.**resize**(*img*, *size*, *interpolation=2*)
resize the image TODO: opencv resize 0~1 Arguments:

img {ndarray} – the input ndarray image size {int, iterable} – the target size, if size is intger, width and height will be resized to same otherwise, the size should be tuple (height, width) or list [height, width]

Keyword Arguments: interpolation {Image} – the interpolation method (default: {Image.BILINEAR})

Raises: TypeError – img should be ndarray ValueError – size should be intger or iterable vaiable and length should be 2.

Returns: img – resize ndarray image

torchsat.transforms.functional.**resized_crop**(*img*, *top*, *left*, *height*, *width*, *size*, *interpolation=2*)

torchsat.transforms.functional.**rotate**(*img*, *angle*, *center=None*, *scale=1.0*)

torchsat.transforms.functional.**rotate_box**(*bboxes*, *angle*, *center_x*, *center_y*)
rotate_box rotate the bboxes

Args: bboxes (ndarray): the original bboxes, N(numbers) x 4 angle (float): rotate angle should be degree center_x (int): rotate center x center_y (int): rotate center y

Returns: ndarray: the rotated bboxes

torchsat.transforms.functional.**shift**(*img*, *top*, *left*)

torchsat.transforms.functional.**to_grayscale**(*img*, *output_channels=1*)
convert input ndarray image to gray sacle image.

Arguments: img {ndarray} – the input ndarray image

Keyword Arguments: output_channels {int} – output gray image channel (default: {1})

Returns: ndarray – gray scale ndarray image

torchsat.transforms.functional.**to_pil_image**(*tensor*)

torchsat.transforms.functional.**to_tensor**(*img*)
convert numpy.ndarray to torch tensor.

if the image is uint8 , it will be divided by 255;

if the image is uint16 , it will be divided by 65535;

if the image is float , it will not be divided, we suppose your image range should between [0~1] ;

Arguments: img {numpy.ndarray} – image to be converted to tensor. torch.float32

torchsat.transforms.functional.**to_tiff_image**(*tensor*)

torchsat.transforms.functional.**vflip**(*img*)

torchsat.transforms.transforms_cls module

class torchsat.transforms.transforms_cls.**Compose**(*transforms*)
Bases: object

Composes serveral classification transform together.

Args: transforms (list of `transform` objects): list of classification transforms to compose.

Example:

```
>>> transforms_cls.Compose([
>>>     transforms_cls.Resize(300),
>>>     transforms_cls.ToTensor()
>>>     ])
```

class torchsat.transforms.transforms_cls.**Lambda**(*lambd*)
Bases: object

Apply a user-defined lambda as function.

Args: lambd (function): Lambda/function to be used for transform.

class torchsat.transforms.transforms_cls.**ToTensor**
Bases: object

onvert numpy.ndarray to torch tensor.

if the image is uint8 , it will be divided by 255; if the image is uint16 , it will be divided by 65535; if the image is float , it will not be divided, we suppose your image range should between [0~1] ;

Args: img {numpy.ndarray} – image to be converted to tensor.

class torchsat.transforms.transforms_cls.**Normalize**(*mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225], inplace=False*)
Bases: object

Normalize a tensor image with mean and standard deviation.

Given mean: `(M1,...,Mn)` and std: `(S1,..,Sn)` for `n` channels, this transform will normalize each channel of the input `torch.*Tensor` i.e. `input[channel] = (input[channel] - mean[channel]) / std[channel]` .. note:

```
This transform acts out of place, i.e., it does not mutates the input tensor.
```

Args: tensor (tensor): input torch tensor data. mean (sequence): Sequence of means for each channel. std (sequence): Sequence of standard deviations for each channel. inplace (boolean): inplace apply the transform or not. (default: False)

class torchsat.transforms.transforms_cls.**ToGray**(*output_channels=1*)
Bases: object

Convert the image to grayscale

Args: output_channels (int): number of channels desired for output image. (default: 1)

Returns: [ndarray]: the graysacle version of input - If output_channels=1 : returned single channel image (height, width) - If output_channels>1 : returned multi-channels ndarray image (height, width, channels)

class torchsat.transforms.transforms_cls.**GaussianBlur**(*kernel_size=3*)
Bases: object

Convert the input ndarray image to blurred image by gaussian method.

Args: kernel_size (int): kernel size of gaussian blur method. (default: 3)

Returns: ndarray: the blurred image.

class torchsat.transforms.transforms_cls.**RandomNoise**(*mode='gaussian'*, *percent=0.02*)

Bases: object

Add noise to the input ndarray image. Args:

mode (str): the noise mode, should be one of gaussian, salt, pepper, s&p, (default: gaussian).
percent (float): noise percent, only work for salt, pepper, s&p mode. (default: 0.02)

Returns: ndarray: noised ndarray image.

class torchsat.transforms.transforms_cls.**RandomBrightness**(*max_value=0*)

Bases: object

class torchsat.transforms.transforms_cls.**RandomContrast**(*max_factor=0*)

Bases: object

class torchsat.transforms.transforms_cls.**RandomShift**(*max_percent=0.4*)

Bases: object

random shift the ndarray with value or some percent.

Args: max_percent (float): shift percent of the image.

Returns: ndarray: return the shifted ndarray image.

class torchsat.transforms.transforms_cls.**RandomRotation**(*degrees*, *center=None*)

Bases: object

random rotate the ndarray image with the degrees.

Args:

degrees (number or sequence): the rotate degree. If single number, it must be positive. if squeence, it's length must 2 and first number should small than the second one.

Raises: ValueError: If degrees is a single number, it must be positive. ValueError: If degrees is a sequence, it must be of len 2.

Returns: ndarray: return rotated ndarray image.

class torchsat.transforms.transforms_cls.**Resize**(*size*, *interpolation=2*)

Bases: object

resize the image Args:

img {ndarray} : the input ndarray image size {int, iterable} : the target size, if size is intger, width and height will be resized to same otherwise, the size should be tuple (height, width) or list [height, width]

Keyword Arguments: interpolation {Image} : the interpolation method (default: {Image.BILINEAR})

Raises: TypeError : img should be ndarray ValueError : size should be intger or iterable vaiable and length should be 2.

Returns: img (ndarray) : resize ndarray image

class torchsat.transforms.transforms_cls.**Pad**(*padding*, *fill=0*, *padding_mode='constant'*)

Bases: object

Pad the given ndarray image with padding width. Args:

padding [{int, sequence}, padding width] If int, each border same. If sequence length is 2, this is the padding for left/right and top/bottom. If sequence length is 4, this is the padding for left, top, right, bottom.

fill: {int, sequence}: Pixel padding_mode: str or function. contain{'constant','edge','linear_ramp','maximum','mean'

, 'median', 'minimum', 'reflect','symmetric','wrap'} (default: constant)

Examples:

```
>>> transformed_img = Pad(img, 20, mode='reflect')
>>> transformed_img = Pad(img, (10,20), mode='edge')
>>> transformed_img = Pad(img, (10,20,30,40), mode='reflect')
```

class torchsat.transforms.transforms_cls.**CenterCrop**(*out_size*)
Bases: object

crop image

Args: img {ndarray}: input image output_size {number or sequence}: the output image size. if sequence, should be [height, width]

Raises: ValueError: the input image is large than original image.

Returns: ndarray: return croped ndarray image.

class torchsat.transforms.transforms_cls.**RandomCrop**(*size*)
Bases: object

random crop the input ndarray image

Args: size (int, sequence): th output image size, if sequeue size should be [height, width]

Returns: ndarray: return random croped ndarray image.

class torchsat.transforms.transforms_cls.**RandomHorizontalFlip**(*p=0.5*)
Bases: object

Flip the input image on central horizon line.

Args: p (float): probability apply the horizon flip.(default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_cls.**RandomVerticalFlip**(*p=0.5*)
Bases: object

Flip the input image on central vertical line.

Args: p (float): probability apply the vertical flip. (default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_cls.**RandomFlip**(*p=0.5*)
Bases: object

Flip the input image vertical or horizon.

Args: p (float): probability apply flip. (default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_cls.**RandomResizedCrop**(*crop_size*, *target_size*, *interpolation=2*)

Bases: object

[summary]

Args: object ([type]): [description]

Returns: [type]: [description]

class torchsat.transforms.transforms_cls.**ElasticTransform**(*alpha=1*, *sigma=50*, *alpha_affine=50*, *interpolation=1*, *border_mode=4*, *random_state=None*, *approximate=False*)

Bases: object

code modify from https://github.com/albu/albumentations. Elastic deformation of images as described in [Simard2003] (with modifications). Based on https://gist.github.com/erniejunior/601cdf56d2b424757de5 .. [Simard2003] Simard, Steinkraus and Platt, "Best Practices for

> Convolutional Neural Networks applied to Visual Document Analysis", in Proc. of the International Conference on Document Analysis and Recognition, 2003.

Args:

approximate (boolean): Whether to smooth displacement map with fixed kernel size. Enabling this option gives ~2X speedup on large images.

Image types: uint8, uint16 float32

torchsat.transforms.transforms_det module

class torchsat.transforms.transforms_det.**Compose**(*transforms*)

Bases: object

Composes serveral classification transform together.

Args: transforms (list of `transform` objects): list of classification transforms to compose.

Example:

```
>>> transforms_cls.Compose([
>>>     transforms_cls.Resize(300),
>>>     transforms_cls.ToTensor()
>>>     ])
```

class torchsat.transforms.transforms_det.**Lambda**(*lambd*)

Bases: object

Apply a user-defined lambda as function.

Args: lambd (function): Lambda/function to be used for transform.

class torchsat.transforms.transforms_det.**ToTensor**

Bases: object

onvert numpy.ndarray to torch tensor.

> if the image is uint8 , it will be divided by 255; if the image is uint16 , it will be divided by 65535; if the image is float , it will not be divided, we suppose your image range should between [0~1] ;

Args: img {numpy.ndarray} – image to be converted to tensor. bboxes {numpy.ndarray} – target bbox to be converted to tensor. the input should be [box_nums, 4] labels {numpy.ndarray} – target labels to be converted to tensor. the input shape shold be [box_nums]

class torchsat.transforms.transforms_det.**Normalize**(*mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225], inplace=False*)

Bases: object

Normalize a tensor image with mean and standard deviation.

Given mean: `(M1,...,Mn)` and std: `(S1,..,Sn)` for `n` channels, this transform will normalize each channel of the input `torch.*Tensor` i.e. `input[channel] = (input[channel] - mean[channel]) / std[channel]` .. note:

```
This transform acts out of place, i.e., it does not mutates the input tensor.
```

Args: tensor (tensor): input torch tensor data. mean (sequence): Sequence of means for each channel. std (sequence): Sequence of standard deviations for each channel. inplace (boolean): inplace apply the transform or not. (default: False)

class torchsat.transforms.transforms_det.**ToGray**(*output_channels=1*)

Bases: object

Convert the image to grayscale

Args: output_channels (int): number of channels desired for output image. (default: 1)

Returns: [ndarray]: the graysacle version of input - If output_channels=1 : returned single channel image (height, width) - If output_channels>1 : returned multi-channels ndarray image (height, width, channels)

class torchsat.transforms.transforms_det.**GaussianBlur**(*kernel_size=3*)

Bases: object

Convert the input ndarray image to blurred image by gaussian method.

Args: kernel_size (int): kernel size of gaussian blur method. (default: 3)

Returns: ndarray: the blurred image.

class torchsat.transforms.transforms_det.**RandomNoise**(*mode='gaussian', percent=0.02*)

Bases: object

Add noise to the input ndarray image. Args:

mode (str): the noise mode, should be one of `gaussian`, `salt`, `pepper`, `s&p`, (default: gaussian).
percent (float): noise percent, only work for `salt`, `pepper`, `s&p` mode. (default: 0.02)

Returns: ndarray: noised ndarray image.

class torchsat.transforms.transforms_det.**RandomBrightness**(*max_value=0*)

Bases: object

class torchsat.transforms.transforms_det.**RandomContrast**(*max_factor=0*)

Bases: object

class torchsat.transforms.transforms_det.**Resize**(*size, interpolation=2*)

Bases: object

resize the image Args:

img {ndarray} : the input ndarray image size {int, iterable} : the target size, if size is intger, width and height will be resized to same otherwise, the size should be tuple (height, width) or list [height, width]

Keyword Arguments: interpolation {Image} : the interpolation method (default: {Image.BILINEAR})

Raises: TypeError : img should be ndarray ValueError : size should be intger or iterable vaiable and length should be 2.

Returns: img (ndarray) : resize ndarray image

class torchsat.transforms.transforms_det.**Pad**(*padding*, *fill=0*, *padding_mode='constant'*)

Bases: object

Pad the given ndarray image with padding width. Args:

padding [{int, sequence}, padding width] If int, each border same. If sequence length is 2, this is the padding for left/right and top/bottom. If sequence length is 4, this is the padding for left, top, right, bottom.

fill: {int, sequence}: Pixel padding_mode: str or function. contain{'constant','edge','linear_ramp','maximum','mean'

, 'median', 'minimum', 'reflect','symmetric','wrap'} (default: constant)

Examples:

```
>>> transformed_img = Pad(img, 20, mode='reflect')
>>> transformed_img = Pad(img, (10,20), mode='edge')
>>> transformed_img = Pad(img, (10,20,30,40), mode='reflect')
```

class torchsat.transforms.transforms_det.**CenterCrop**(*out_size*)

Bases: object

crop image

Args: img {ndarray}: input image output_size {number or sequence}: the output image size. if sequence, should be [height, width]

Raises: ValueError: the input image is large than original image.

Returns: ndarray: return croped ndarray image.

class torchsat.transforms.transforms_det.**RandomCrop**(*size*)

Bases: object

random crop the input ndarray image

Args: size (int, sequence): th output image size, if sequeue size should be [height, width]

Returns: ndarray: return random croped ndarray image.

class torchsat.transforms.transforms_det.**RandomHorizontalFlip**(*p=0.5*)

Bases: object

Flip the input image on central horizon line.

Args: p (float): probability apply the horizon flip.(default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_det.**RandomVerticalFlip**(*p=0.5*)
Bases: object

Flip the input image on central vertical line.

Args: p (float): probability apply the vertical flip. (default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_det.**RandomFlip**(*p=0.5*)
Bases: object

Flip the input image vertical or horizon.

Args: p (float): probability apply flip. (default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_det.**RandomResizedCrop**(*crop_size*, *target_size*, *interpolation=2*)
Bases: object

[summary]

Args: object ([type]): [description]

Returns: [type]: [description]

torchsat.transforms.transforms_seg module

class torchsat.transforms.transforms_seg.**Compose**(*transforms*)
Bases: object

class torchsat.transforms.transforms_seg.**Lambda**(*lambd*)
Bases: object

class torchsat.transforms.transforms_seg.**ToTensor**
Bases: object

class torchsat.transforms.transforms_seg.**Normalize**(*mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225], inplace=False*)
Bases: object

class torchsat.transforms.transforms_seg.**ToGray**(*output_channels=1*)
Bases: object

Convert the image to grayscale

Args: output_channels (int): number of channels desired for output image. (default: 1)

Returns: [ndarray]: the graysacle version of input - If output_channels=1 : returned single channel image (height, width) - If output_channels>1 : returned multi-channels ndarray image (height, width, channels)

class torchsat.transforms.transforms_seg.**GaussianBlur**(*kernel_size=3*)
Bases: object

class torchsat.transforms.transforms_seg.**RandomNoise**(*mode='gaussian', percent=0.02*)
Bases: object

Add noise to the input ndarray image. Args:

mode (str): the noise mode, should be one of `gaussian`, `salt`, `pepper`, `s&p`, (default: gaussian).
percent (float): noise percent, only work for `salt`, `pepper`, `s&p` mode. (default: 0.02)

Returns: ndarray: noised ndarray image.

class torchsat.transforms.transforms_seg.**RandomBrightness**(*max_value=0*)
Bases: object

class torchsat.transforms.transforms_seg.**RandomContrast**(*max_factor=0*)
Bases: object

class torchsat.transforms.transforms_seg.**RandomShift**(*max_percent=0.4*)
Bases: object

random shift the ndarray with value or some percent.

Args: max_percent (float): shift percent of the image.

Returns: ndarray: return the shifted ndarray image.

class torchsat.transforms.transforms_seg.**RandomRotation**(*degrees*, *center=None*)
Bases: object

random rotate the ndarray image with the degrees.

Args:

degrees (number or sequence): the rotate degree. If single number, it must be positive. if squeence, it's length must 2 and first number should small than the second one.

Raises: ValueError: If degrees is a single number, it must be positive. ValueError: If degrees is a sequence, it must be of len 2.

Returns: ndarray: return rotated ndarray image.

class torchsat.transforms.transforms_seg.**Resize**(*size*, *interpolation=2*)
Bases: object

resize the image Args:

img {ndarray} : the input ndarray image size {int, iterable} : the target size, if size is intger, width and height will be resized to same otherwise, the size should be tuple (height, width) or list [height, width]

Keyword Arguments: interpolation {Image} : the interpolation method (default: {Image.BILINEAR})

Raises: TypeError : img should be ndarray ValueError : size should be intger or iterable vaiable and length should be 2.

Returns: img (ndarray) : resize ndarray image

class torchsat.transforms.transforms_seg.**Pad**(*padding*, *fill=0*, *padding_mode='constant'*)
Bases: object

Pad the given ndarray image with padding width. Args:

padding [{int, sequence}, padding width] If int, each border same. If sequence length is 2, this is the padding for left/right and top/bottom. If sequence length is 4, this is the padding for left, top, right, bottom.

fill: {int, sequence}: Pixel padding_mode: str or function. contain{'constant','edge','linear_ramp','maximum','mean'

, 'median', 'minimum', 'reflect','symmetric','wrap'} (default: constant)

Examples:

```
>>> transformed_img = Pad(img, 20, mode='reflect')
>>> transformed_img = Pad(img, (10,20), mode='edge')
>>> transformed_img = Pad(img, (10,20,30,40), mode='reflect')
```

class torchsat.transforms.transforms_seg.**CenterCrop**(*out_size*)
Bases: object

crop image

Args: img {ndarray}: input image output_size {number or sequence}: the output image size. if sequence, should be [height, width]

Raises: ValueError: the input image is large than original image.

Returns: ndarray: return croped ndarray image.

class torchsat.transforms.transforms_seg.**RandomCrop**(*size*)
Bases: object

random crop the input ndarray image

Args: size (int, sequence): th output image size, if sequeue size should be [height, width]

Returns: ndarray: return random croped ndarray image.

class torchsat.transforms.transforms_seg.**RandomHorizontalFlip**(*p=0.5*)
Bases: object

Flip the input image on central horizon line.

Args: p (float): probability apply the horizon flip.(default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_seg.**RandomVerticalFlip**(*p=0.5*)
Bases: object

Flip the input image on central vertical line.

Args: p (float): probability apply the vertical flip. (default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_seg.**RandomFlip**(*p=0.5*)
Bases: object

Flip the input image vertical or horizon.

Args: p (float): probability apply flip. (default: 0.5)

Returns: ndarray: return the flipped image.

class torchsat.transforms.transforms_seg.**RandomResizedCrop**(*crop_size*, *target_size*, *interpolation=2*)
Bases: object

[summary]

Args: object ([type]): [description]

Returns: [type]: [description]

class torchsat.transforms.transforms_seg.**ElasticTransform**(*alpha=1*, *sigma=50*, *alpha_affine=50*, *interpolation=1*, *border_mode=4*, *random_state=None*, *approximate=False*)

Bases: object

code modify from https://github.com/albu/albumentations. Elastic deformation of images as described in [Simard2003] (with modifications). Based on https://gist.github.com/erniejunior/601cdf56d2b424757de5 .. [Simard2003] Simard, Steinkraus and Platt, "Best Practices for

> Convolutional Neural Networks applied to Visual Document Analysis", in Proc. of the International Conference on Document Analysis and Recognition, 2003.

Args:

approximate (boolean): Whether to smooth displacement map with fixed kernel size. Enabling this option gives ~2X speedup on large images.

Image types: uint8, uint16 float32

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torchsat.utils package

Submodules

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9.1.2 Module contents

CHAPTER 10

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