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NATIONAL INSTITUTE OF TECHNOLOGY

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

Image Segmentation with Machine Learning

Intern Project Report

Semester VII

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CERTIFICATE

This is to certify that the intern project report carried out on "**Image Segmentation with Machine Learning**"

By Pranshu kumar choudhary

Have successfully completed their intern project in partial fulfilment of their Degree in Bachelor of Technology in Computer Science and Engineering.

03/12/2020

Dr. Praveen Kaushik

DECLARATION

We, hereby declare that the following report which is being presented in the Project Documentation Entitled as “Image segmentation with machine learning” is an authentic documentation of our own original work and to best of our knowledge. The following project and its report, in part or whole, has not been presented or submitted by us for any purpose in any other institute or organization. Any contribution made to the research by others, with whom we have worked at Maulana Azad National Institute of Technology, Bhopal or elsewhere, is explicitly acknowledged in the report.

Pranshu kumar choudhary
SN : 171112297
Date : 11/11/2020

Pranshu

ACKNOWLEDGEMENT

With due respect, we express our deep sense of gratitude to our respected guide and coordinator Dr. Praveen Kaushik, for her valuable help and guidance. We are thankful for the encouragement that she has given us in completing this project successfully.

It is imperative for us to mention the fact that the report of project could not have been accomplished without the periodic suggestions and advice of our project guide Dr. Praveen Kaushik .

We are also thankful to all the other faculty, staff members and laboratory attendants of our department for their kind cooperation and help. Last but certainly not the least; we would like to express our deep appreciation towards our family members and batch mates for providing the much needed support and encouragement.

ABSTRACT

We might have wondered, how fast and efficiently our brain is trained to identify and classify what our eyes perceive. Somehow our brain is trained in a way to analyze everything at a granular level. This helps us distinguish an apple in a bunch of oranges.

Computer vision is a field of computer science that enables computers to identify and process objects in videos and images just the way we humans do. Although computer vision might seem like not a very old concept but it dates back to the late 1960s when the first digital image scanner which transformed images into grids of numbers was invented.

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INTRODUCTION

We would have probably heard about object detection and image localization. When there is a single object present in an image, we use image localization technique to draw a bounding box around that object. In the case of object detection, it provides labels along with the bounding boxes; hence we can predict the location as well as the class to which each object belongs.

Image segmentation results in more granular information about the shape of an image and thus an extension of the concept of Object Detection.

We segment i.e. divide the images into regions of different colors which helps in distinguishing an object from the other at a finer level

Types of Image Segmentation

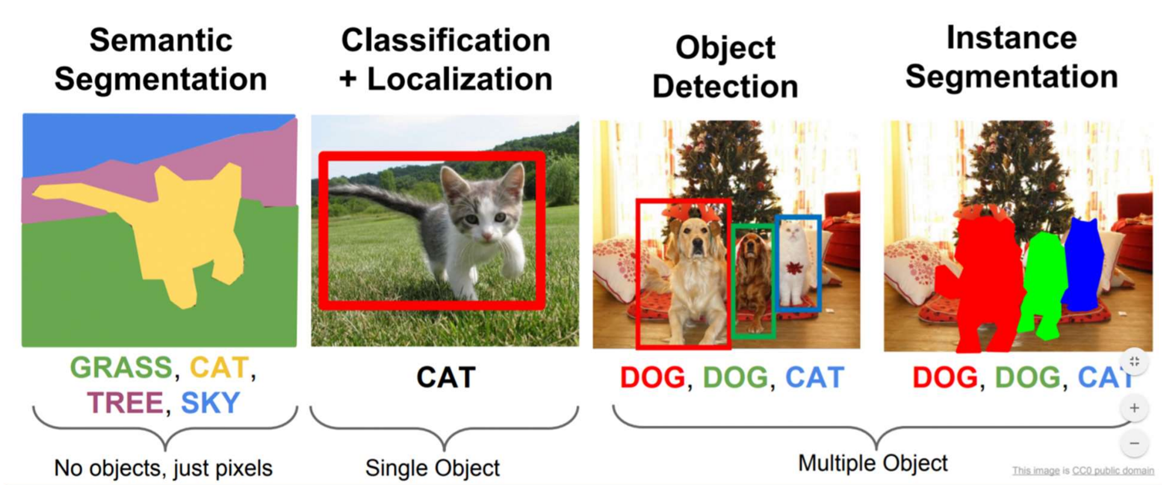


Image Segmentation can be broadly classified into two types:

Semantic Segmentation

Semantic Segmentation is the process of segmenting the image pixels into their respective classes. For example, in the figure above, the cat is associated with yellow color; hence all the pixels related to the cat are colored yellow. Multiple objects of the same class are considered as a single entity and hence represented with the same color.

Instance Segmentation

Instance segmentation is being more thorough and usually comes into picture when dealing with multiple objects. The difference here is, the detected object is masked with a color hence all the pixels associated with the image are given the same color. Multiple objects of the same class are treated as distinct entities and hence represented with different colors.

Image Segmentation Applications

1. Self-driving cars

Image segmentation can be used in self-driving cars for giving easy distinctions between various objects. Be it traffic signals, signboards, humans, and cars. It can help the driving instruction algorithm to better assess the surrounding before generating the next instruction

2. Circuit Board Defect Detection

A company has to bear the responsibility of defected devices. If a camera backed with an Image Segmentation model keeps scanning for defects produced in the final product, a lot of money and time can be saved in fixing a defective device.

3. Face detection

Nowadays, we have observed that the majority of cameras in phones support portrait mode. Portrait mode is technically an outcome of Image Segmentation. Apart from this, security surveillance will be much more effective when the faces are distinguishable from noisy objects.

4. Medical Imaging

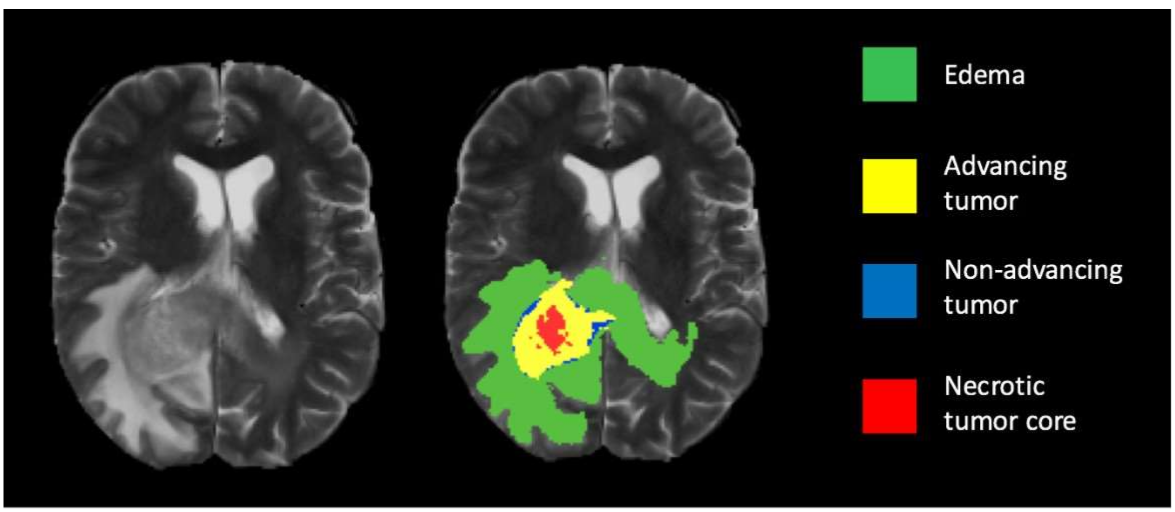


Image segmentation can be used to extract clinically relevant information from medical reports. For example, image segmentation can be used to segment tumors.

Mask R-CNN

We are going to perform image segmentation using the Mask R-CNN architecture. It is an extension of the Faster R-CNN Model which is preferred for object detection tasks.

The Mask R-CNN returns the binary object mask in addition to class label and object bounding box. Mask R-CNN is good at pixel level segmentation.

How does Mask R-CNN work?

Mask R-CNN uses an architecture similar to its predecessor Faster R-CNN and also utilizes Fully Convolutional Network for pixel-wise segmentation.

1. Feature Extraction

We utilize the ResNet 101 architecture to extract features from the input image. As a result, we get feature maps which are transmitted to Region Proposed Network

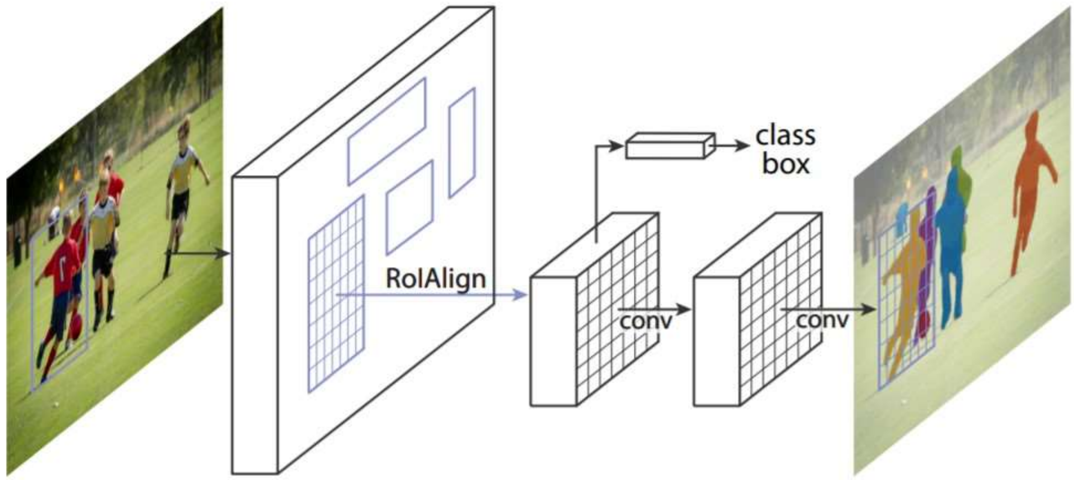
2. Region Proposed Network (RPN)

After obtaining the feature maps, bounding box candidates are determined and thus RPN extracts RoI (Region of Interest)

3. RoI Pool

Faster R-CNN uses an RoI Pool layer to compute features from the obtained proposals in order to infer the class of the object and bounding box coordinates.

4. RoI Align



RoI pool led to misalignments in getting the Region of Interest due to quantization of RoI coordinates. Since pixel-level segmentation required specificity hence authors of the Faster R-CNN cleverly solved it by implementing the RoI Align.

Masking is done by a small fully-connected network applied to each RoI, which predicts a segmentation mask in a pixel-to-pixel manner.

5. Tools and technologies used

Software requirement

The various tools and technologies to be used are as follows:

I) Python Libraries to implement Machine Learning Models -

• Pandas - pandas is a software library written for the Python programming language for data manipulation and analysis.

• NumPy - NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.

Scikit learn - Scikit is an open source Python library that implements a range of machine learning, pre-processing, cross-validation and visualization algorithms using a unified interface.

• To build the machine learning models we used The Jupyter Notebook. Jupyter Notebook is an open-source web application that can be used to implement statistical modelling, data visualization, machine learning etc.

Hardware requirement

Working Computer system

Processor Requirement: Intel I3 core and above.

Memory Requirement: 4GB and above.

Steps to develop Image Segmentation Project

1. Clone Mask R-CNN Github Repository

Now, primarily we download the architecture of the model which we are going to implement. Use the following command:

git clone: https://github.com/matterport/Mask_RCNN.git

Note : If you do not have git installed on your computer, then simply download the file in zip and extract the folder in your desired directory.

2. Library Dependencies

Now, since we need certain libraries in order to make it work as you might not have all the necessary libraries.

- numpy
- scipy
- pillow
- cython
- matplotlib
- scikit-image
- tensorflow
- keras
- opencv-python
- h5py
- imgaug
- ipython

3. Pre Trained Weights

Since training a model takes hours and sometimes a day or more, hence it may not be feasible to train a model right now. Hence, we will utilize the pre-trained model to generate predictions on our input image.

I have used **Mask R-CNN 2.0**. We can directly download the **h5 file** and save it in the samples folder of the Mask R-CNN repository we cloned in the first step.

4. Make a new Jupyter Notebook

So far, we have assembled the engine, it’s time to utilize the power of our engine and drive all the way to our segmented image.

Now, we will make a new Jupyter Notebook under the samples folder in Mask R-CNN repository, you can use any other IDE but Jupyter Notebook gives the ease to execute code cell by cell.

If you do not have a powerful system, you can use **google colab** for running the code, but make sure to upload the repo and h5 file correctly.

5. Importing the Necessary Libraries

```
import os
import sys
import random
import math
import numpy as np
import skimage.io
import matplotlib
import matplotlib.pyplot as plt

# Fetching the root directory
ROOT_DIR = os.path.abspath("../")

import warnings
warnings.filterwarnings("ignore")

# Importing Mask RCNN
sys.path.append(ROOT_DIR)  # To find local version of the library
from mrcnn import utils
import mrcnn.model as modellib
from mrcnn import visualize

# Heading to the coco directory
sys.path.append(os.path.join(ROOT_DIR, "samples/coco/"))
#importing coco.py
import coco
%matplotlib inline
```

6. The path for pretrained weights

```
# Directory to save logs and trained model
```

```
MODEL_DIR = os.path.join(ROOT_DIR, "logs")

# Local path to trained weights file
COCO_MODEL_PATH = os.path.join('', "mask_rcnn_coco.h5")

# Directory of images to run detection on
DIR_IMAGE = os.path.join(ROOT_DIR, "images")
```

7. Inference class to infer the Mask R-CNN Model

```
class InferenceConfig(coco.CocoConfig):
    # Setting batch size equal to 1 since we'll be running inference on
    # one image at a time. Batch size = GPU_COUNT * IMAGES_PER_GPU
    GPU_COUNT = 1
    IMAGES_PER_GPU = 1

config = InferenceConfig()
config.display()
```

Output:

```
Configurations:
BACKBONE                       resnet101
BACKBONE_STRIDES               [4, 8, 16, 32, 64]
BATCH_SIZE                     1
BBOX_STD_DEV                   [0.1 0.1 0.2 0.2]
COMPUTE_BACKBONE_SHAPE         None
DETECTION_MAX_INSTANCES        100
DETECTION_MIN_CONFIDENCE       0.7
DETECTION_NMS_THRESHOLD        0.3
FPN_CLASSIF_FC_LAYERS_SIZE     1024
GPU_COUNT                      1
GRADIENT_CLIP_NORM             5.0
IMAGES_PER_GPU                 1
IMAGE_CHANNEL_COUNT            3
IMAGE_MAX_DIM                  1024
IMAGE_META_SIZE                93
IMAGE_MIN_DIM                  800
IMAGE_MIN_SCALE                0
IMAGE_RESIZE_MODE              square
IMAGE_SHAPE                    [1024 1024    3]
LEARNING_MOMENTUM              0.9
LEARNING_RATE                  0.001
LOSS_WEIGHTS                   {'rpn_class_loss': 1.0, 'rpn_bbox_loss': 1.0, 'mrcnn_class_loss': 1.0, 'mrcnn_bbox_loss': 1.0,
'mrcnn_mask_loss': 1.0}
MASK_POOL_SIZE                 14
MASK_SHAPE                     [28, 28]
MAX_GT_INSTANCES               100
MEAN_PIXEL                     [123.7 116.8 103.9]
MINI_MASK_SHAPE                (56, 56)
NAME                           coco
NUM_CLASSES                    81
POOL_SIZE                      7
POST_NMS_ROIS_INFERENCE        1000
POST_NMS_ROIS_TRAINING         2000
PRE_NMS_LIMIT                  6000
ROI_POSITIVE_RATIO             0.33
RPN_ANCHOR_RATIOS              [0.5, 1, 2]
RPN_ANCHOR_SCALES              (32, 64, 128, 256, 512)
RPN_ANCHOR_STRIDE              1
RPN_BBOX_STD_DEV               [0.1 0.1 0.2 0.2]
RPN_NMS_THRESHOLD              0.7
RPN_TRAIN_ANCHORS_PER_IMAGE    256
STEPS_PER_EPOCH                1000
TOP_DOWN_PYRAMID_SIZE          256
TRAIN_BN                       False
TRAIN_ROIS_PER_IMAGE           200
USE_MINI_MASK                  True
USE_RPN_ROIS                   True
VALIDATION_STEPS               50
WEIGHT_DECAY                   0.0001
```

We are seeing is the specification of the Mask R-CNN model we are going to use. The backbone is **resnet101** which helps in extracting features from the image.

Next important thing to observe here is the mask shape which is 28×28 as it is trained on the COCO dataset and we have a total of 81 classes.

This means that there are 81 possible prediction classes in which an object may fall into.

8. Loading the Weights

```
# Create model objects in inference mode.
model = modellib.MaskRCNN(mode="inference", model_dir='mask_rcnn_coco.hy', config=config)

# Load weights trained on MS-COCO
model.load_weights('mask_rcnn_coco.h5', by_name=True)
```

9. Loading an Image to Test the Model

```
image = skimage.io.imread('../images/4410436637_7b0ca36ee7_z.jpg')

# original image
plt.figure(figsize=(12,10))

skimage.io.imshow(image)
```

Output:

```
<matplotlib.image.AxesImage at 0x1fc4b852b70>
```

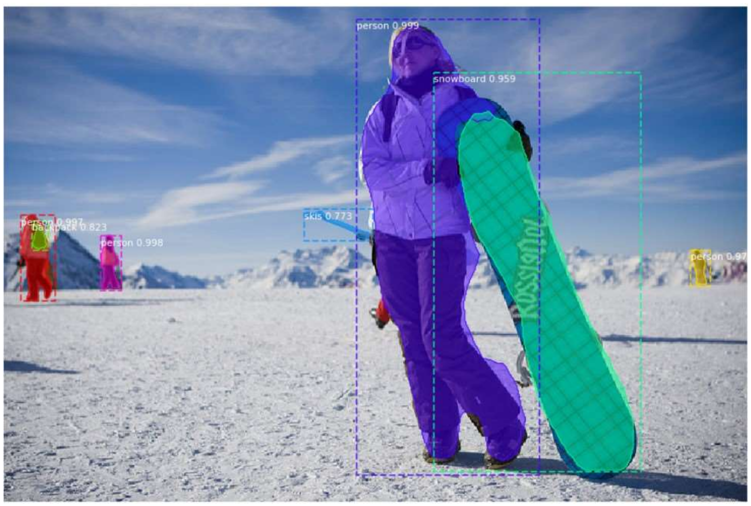
10. Sending Image to Model to Generate Predict

```
# Run detection
results = model.detect([image], verbose=1)
```

12. Masking the Results to our Image

```
# Visualize results
r = results[0]
visualize.display_instances(image, r['rois'], r['masks'], r['class_ids'],
```

The Time you were Desperately waiting, here comes our **Output:**



We have successfully segmented the image and we can see our code has performed pretty well. So cheers to you if you made it through.

13. Number of Detected Objects

```
mask = r['masks']
mask = mask.astype(int)
mask.shape
```

Output:

(426, 640, 7)

Result and conclusion

Here, we can see that there are a total of 7 objects detected by our model on the image.

NOTE: Image & Video Source: Cornell University, Stanford University, Githu

We hope we were able to lead you towards the solution of your first image segmentation problem. we discussed the process and if you are curious to know the details there is plenty of information available on the internet.

We would suggest you read and understand various architectures including the Mask R-CNN we implemented. It will help you analyze things better and also help you to generate new ideas to solve complex problems.

10. References

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