Department of Computing

Imperial College of Science, Technology and Medicine

Image Segmentation

Lecture about Segmentation evaluation methods as well as base-line theory surrounding segmentation. This week's paper is [1]

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Contents

1 Semantic Segmentation

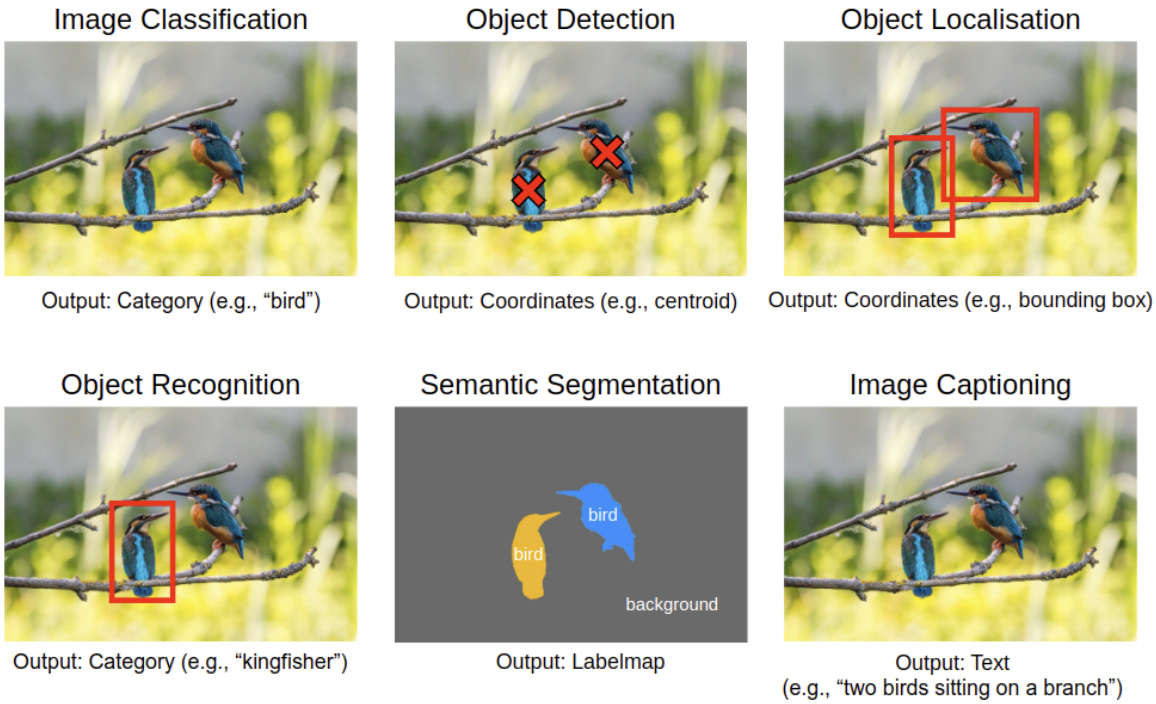


Figure 1: Common image analysis tasks

Definition 1.1 (Semantic Segmentation)**.** Given an input image, we want to label individaul pixels in the image accroding to which object or class they blong to. It is a dense classification where every pixel is being assigned to a specific class.

Each segmented region is assigned a semantic meaning (which contrasts the segmentation based on ‘pure’ clustering of the image into coherent regions).

1.1 Uses

- conducting quantitative analysis, e.g. measuring the volume of a ventricular cavity
- determining the precise location and extent of an organ or certain type of tissue, e.g. a tumour, for treatment such as radiation therapy
- creating 3D models used for simulation, e.g. genrating a model of an abdominal aortic aneurysm for simulating stress/strain distributions

2 Challenges

2.1 noise

Noise in images refers to high-frequency pixel variability which is not relevant, or may obscure, the model’s task.

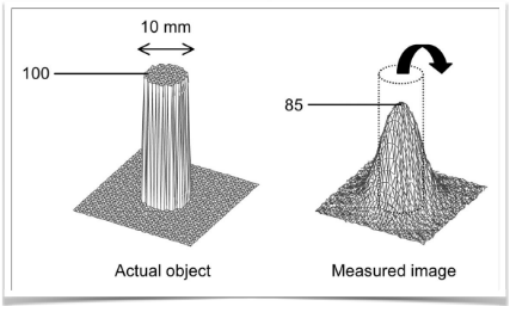
2.2 partical volume effects

The image produced by software is a quantized version of the object. Due to the coarse sampling, the resulting image shows partial volume effects at the boundary of the image. These pixels are not

aligned with real world boundaries. Therefore, the pixels contain a mixture of two different objects.

An object may also be elevated, and it is therefore difficult to measure where the extent of the obejct is because it is unclear where the object starts or ends.

(a) Pixel mixing between boundaries



(b) Elevated region

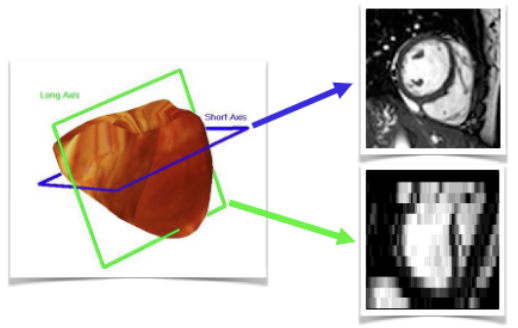
Figure 2: Partial volume effects

2.3 Intensity Inhomogeneities

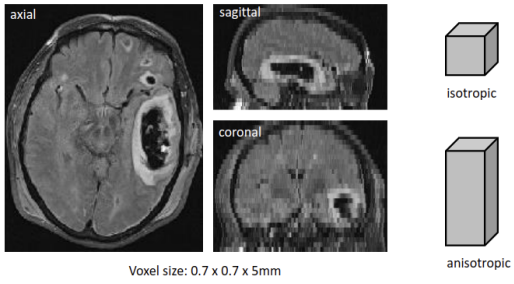
You have the problem that ou might have varying contrast and intensity differences across the image plain. In an ultrasound, the images are acquired from a sensor that sends ultrasound waves into the body so that they may be absorbed by the tissue. This causes lower levels to appear darker on the scan. However, the further down you go, the less signal you get back. Similarly, in an MRI we also have contrasting areas accross the iamge.

2.4 Anisostropic Resolution

Often 2D stacks (x-y dimension) will have high resolution, however, in the z dimension the resolution may be larger, which causes less clarity when looking along this view.



(a) An MRI acquisition of short axis slices of the left ventricle may have an intraslice resolution of 1.3mm and an interslice resolution of 8mm



(b) Anisotropic resolution with french-fry boxes

2.5 Imaging Artifacts

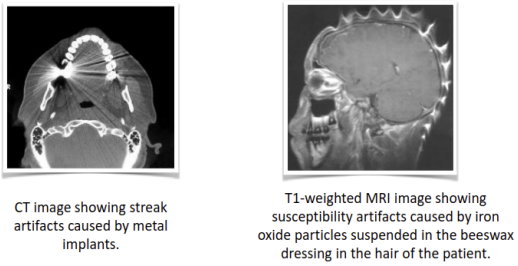


Figure 3: Image artifacts

2.6 limited contrasts

Different tissues can have simlar physical properties and thus similar intesity values. Purely intensity-based algorithms are prone to fail or “leak” into adjacent tissues.

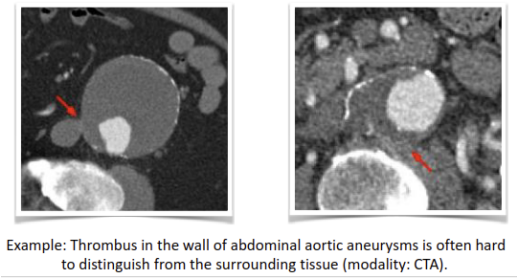


Figure 4: Limited contrast

2.7 Morphological Variability

There is variability between structures we want to segment. It makes it hard to incorporate meaningful prior information or useful shape models.

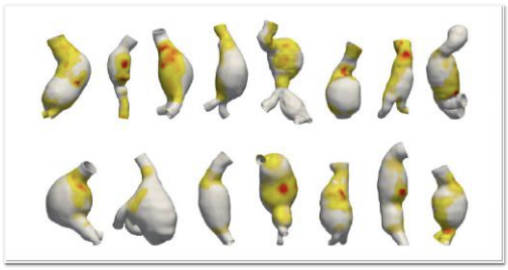


Figure 5: Morphological variablity. A collectino of abdominal aortic aneurysms acquired with PET-CT and colored by FDG-18 uptake values

3 Segmentation Evaluation

3.1 Ground truth

Definition 3.1. Reference or standard against which a method can be comapred, e.g. the otpimal transformation, or a true segmentaiton boundary.

In practice, it is difficult to obtain. We can establish a ground truth with synthetically obtained data, for example, simulated phantoms or around structures we manufactured, such as gel phantoms.

3.2 Gold standard

Usually, an expert manually segments an image.
The disadvantage, is that it

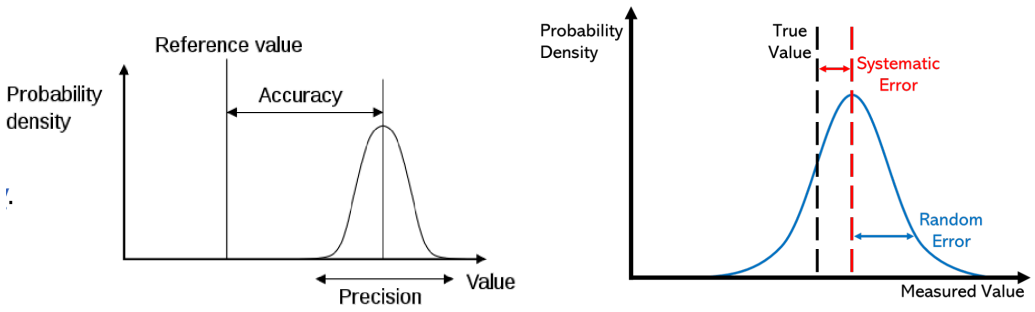
- requires training and is a tedious and time-consuming process.
- There is also intra-oberver variability (disagreement between same obserer on different occasions)
- and inter-observer variability (disagreement between observers)

The remedy, is that

- human observers can perform segmentation repeatedly.
- Multiple experts can perform segmentations,
- agreement or disagreement can be quantified

3.3 Evaluation Metrics

3.3.1 Precision



Is a description of random errors, a measure of statistical variability. It is the repeatbility or reproducibility of the measurement.

3.3.2 Accuracy

More commonly, it is a description of systematic errors, a measure of statistical bias; as these cause a difference between a result and a “true” value, ISO calls this *trueness*.
Alternatively, ISO defines accuracy as describing a combination of both types of observational error above (random and systematic), so high accuracy requires both high precision and high trueness.

3.3.3 Robustness

The degradation in performance with respect to varying noise levels or varying artefacts.

3.3.4 Confusion matrix

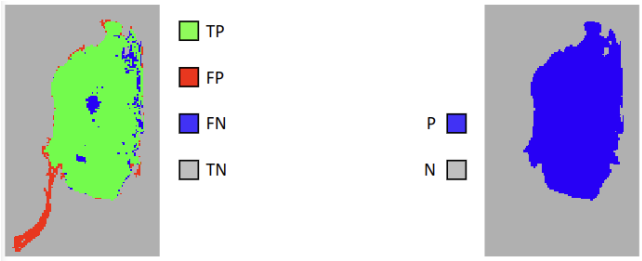


Figure 6: confusion matrix with TP true positive, TN correct rejection, FP false alarm, type I error, FN miss, type II error. Also, P is the number of real positive cases in the dataset, N is the number of real negative cases in the data.

3.3.5 Accuracy

Definition 3.2 (Accuracy)**.**

$$\frac{TP+TN}{P+N} = \frac{TP+TN}{(TP+FN)+(TN+FP)}$$

3.3.6 Precision — positive predicttive value

Definition 3.3 (Precision)**.**

$$\frac{TP}{TP+FP}$$

3.3.7 Recall — sensitivity — hit rate — true positive rate

Definition 3.4 (Recall)**.**

$$\frac{TP}{TP+FN}$$

3.3.8 Specificity — True negative rate

Definition 3.5 (Specificity)**.**

$$\frac{TN}{N} = \frac{TN}{TN+FP}$$

3.3.9 F1 score

Definition 3.6 (F1 score)**.**

$$2\frac{Precision \cdot Recall}{Precision + Recall} = \frac{2TP}{2TP+FP+FN}$$

It is tough to use two metrics independently, it is the harmonic mean between the two.

3.3.10 'IoU' - Overlap based - Jaccard Index

Definition 3.7 (Jaccard Index — Intersection over Union)**.**

$$\frac{|A \cap B|}{|A \cup B|}$$

3.3.11 'DSC' - Overlap based - Dice Similarity

The most widely used measure for evaluating segmentation. Assume that A is the reference, and B is the prediction. Therefore, with $|A| = TP + FN$ and $|B| = TP + FP|$, DSC is equivalent to F1.

Definition 3.8 (DICE)**.**

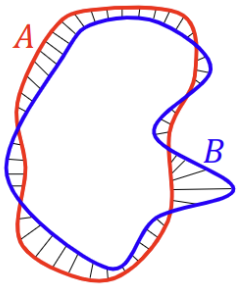
$$2\frac{|A \cap B|}{|A| + |B|}$$

3.3.12 Volume similarity

Definition 3.9 (Volume similarity)**.**

$$1 - \frac{||A| - |B||}{|A| + |B|} = 1 - \frac{|FN - FP|}{2TP + FP + FFN}$$

3.3.13 'HD' - Surface Hasudorff distance



Definition 3.10 (Hausdorff distance)**.**

$$\max(h(A,B), h(B,A)), \quad h(A,B) = \max_{a \in A} \min_{b \in B} ||a - b||$$

3.3.14 'ASSD' - Surface (symmetric) average surface distance

Definition 3.11 (Average surface distance)**.**

$$ASD = \frac{d(A,B) + d(B,A)}{2}, \quad d(A,B) = \frac{1}{N} \sum_{a \ inA} \min_{b \in B} ||a - b||$$

3.4 Pitfalls in segmentation evlauation

"In a field such as athletics, this process is straightforward because the performance measurements (e.g., the time it takes an athlete to run a given distance) exactly reflect the underlying interest (e.g., which athlete runs a given distance the fastest?) [...] If the performance of an image analysis algorithm is not measured according to relevant validation metrics, no reliable statement can be made about the suitability of this algorithm in solving the proposed task, and the algorithm is unlikely to ever reach the stage of real-life application" [2].

3.4.1 Effect of structure size

"The Mask IoU (second column) is less sensitive to boundary errors for large objects. The Boundary IoU (third and fourth column) especially considers contours, (1) yields smaller metric scores, thus

penalizing errors in the boundaries, and (2) is more invariant to structure sizes, leading to very similar values for large and small structures (fourth column). This pitfall is also relevant for other overlap-based metrics" [2]

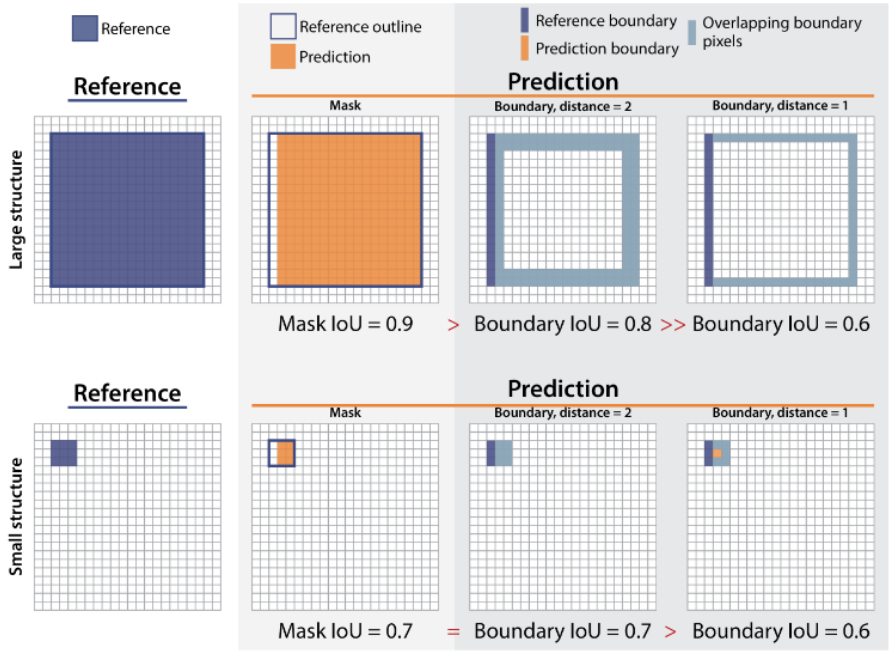


Figure 7: Extended Data Fig. SN 2.12 [2]

"Large structures completely dominate overlap-based metrics in semantic segmentation problems. While Prediction 1 perfectly segments all three small structures, the metric score (here: Dice Similarity Coefficient (DSC)) is much worse compared to the score of Prediction 2, with only one perfect prediction for the large structure. This is highlighted by only computing the metric without the large structure. This pitfall is also relevant for other overlap-based metrics." [2]

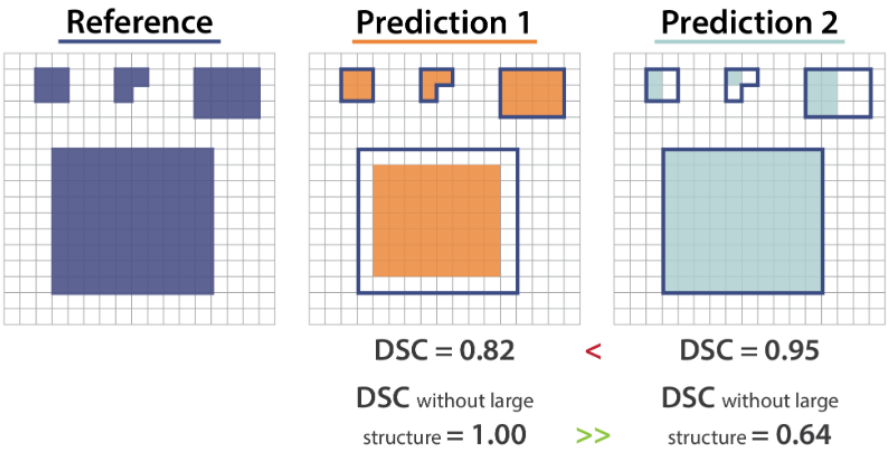
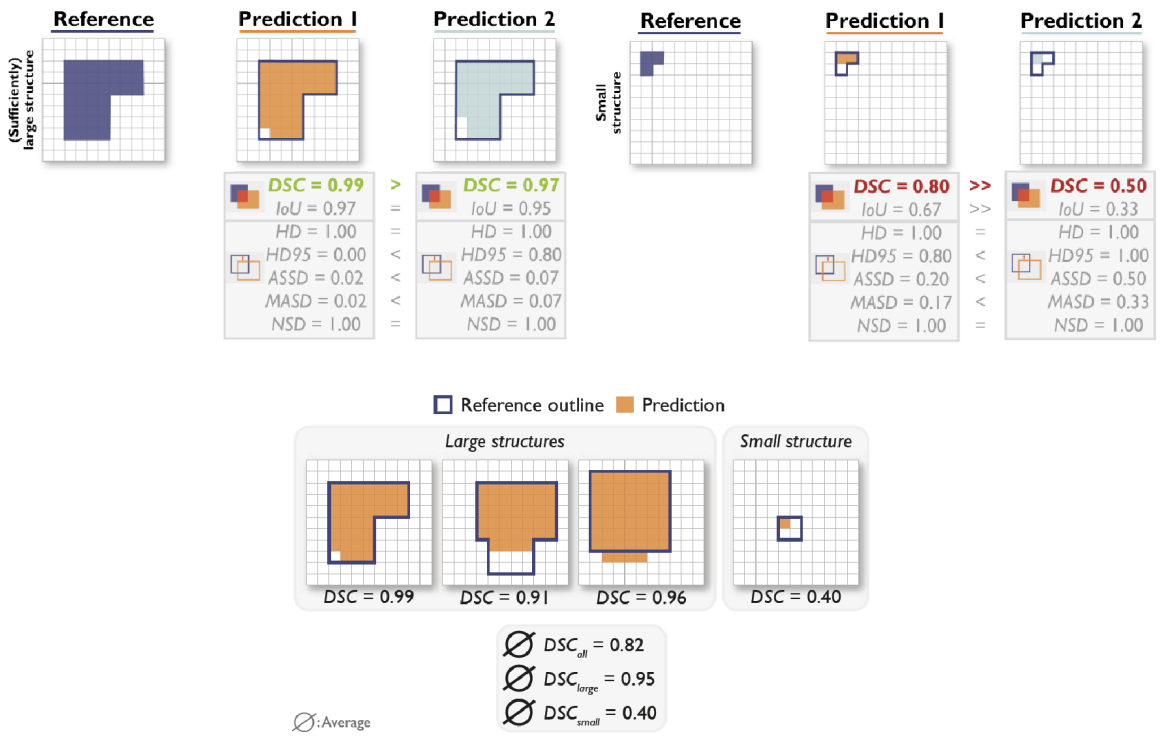


Figure 8: Extended Data Fig. SN 2.13 [2]



3.4.2 Effect of structure shape

"Common overlap-based metrics such as the Dice Similarity Coefficient (DSC) are unaware of complex structure shapes and treat Predictions 1 and 2 equally. The centerline Dice Similarity Coefficient (clDice) uncovers that Prediction 1 misses the fine-granular branches of the reference and favors Prediction 2, which focuses on the object's center line and better captures its fine branches. This pitfall is also relevant for other overlap-based metrics" [2]

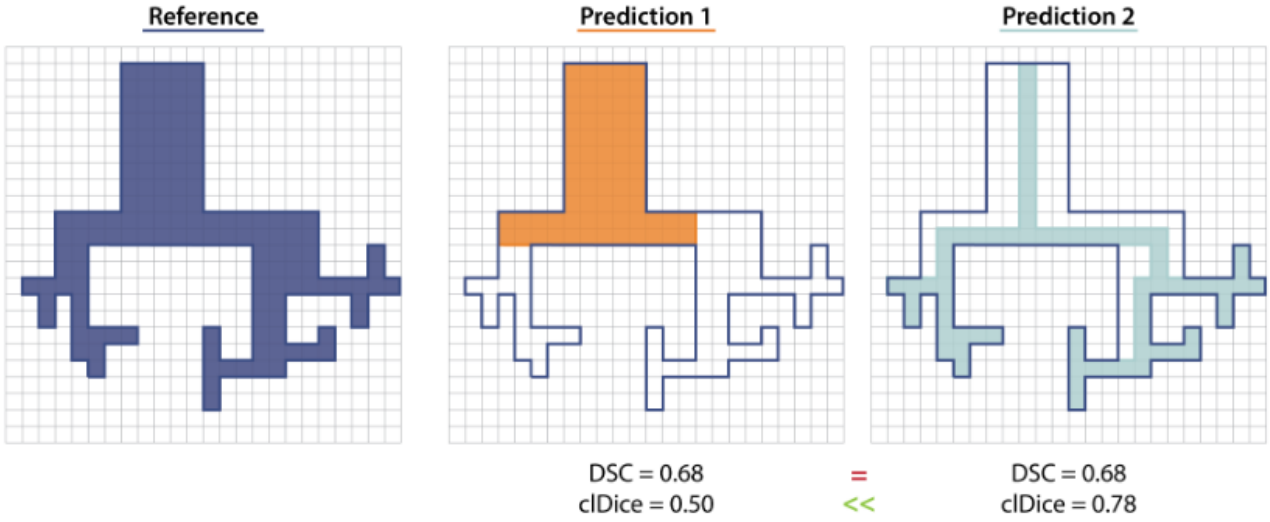
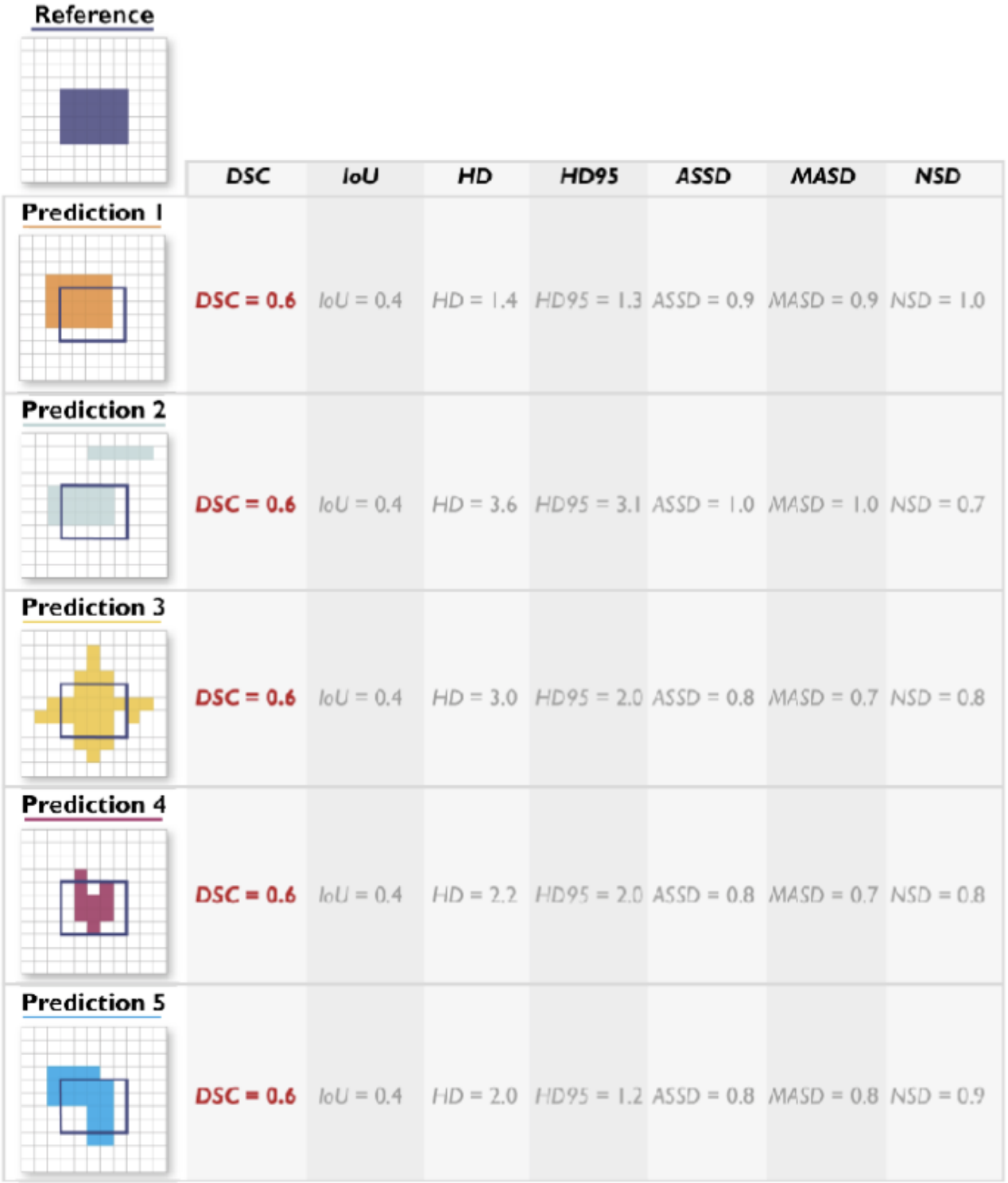


Figure 9: Extended Data Fig. Sn 2.14 [2]



3.4.3 Effect of spatial alignment

"The most common counting-based metrics are poor proxies for the center point alignment. Here, Predictions 1 and 2 yield the same Dice Similarity Coefficient (DSC) value although Prediction 1 approximates the location of the object much better" [2]. This pitfall is also reveleant for other boundary and overla-based metrics such as Boundary Intersection over Union (IoU) and Hasudorff Distance (HD).

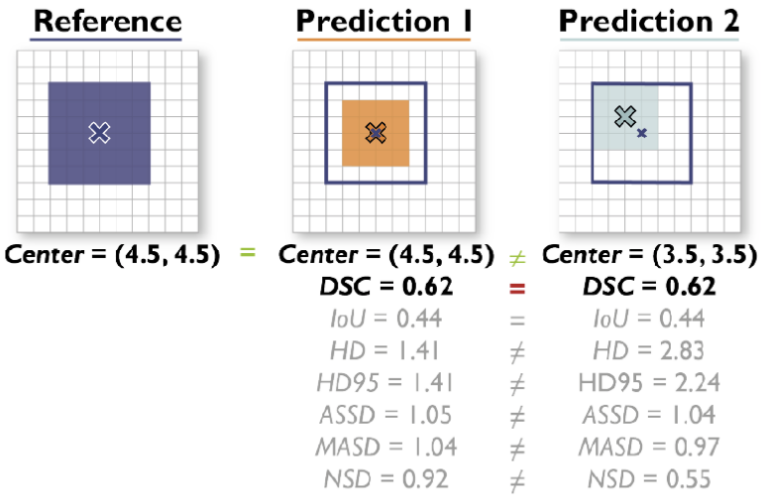


Figure 10: Extended Data Fig. SN 2.7 [2]

3.4.4 Effect of holes

Boundary-based metrics commonly ignore the overlap between structures and are thus insensitive to holes in structures.

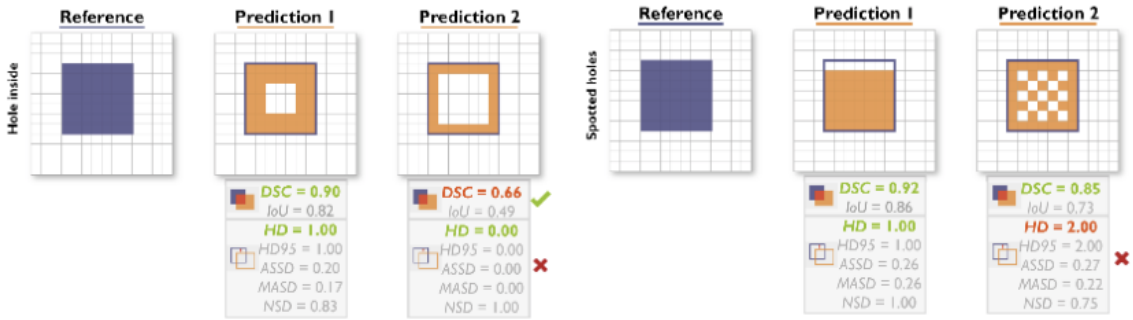
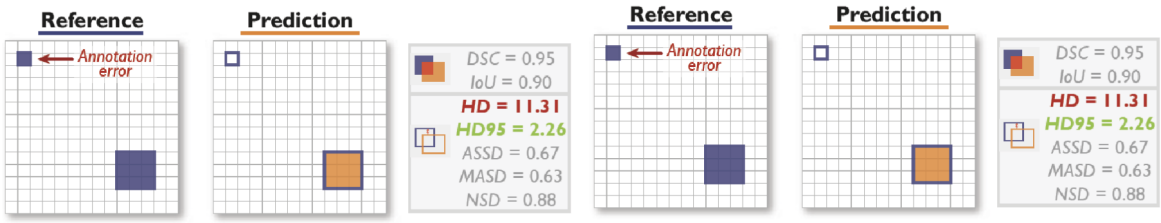
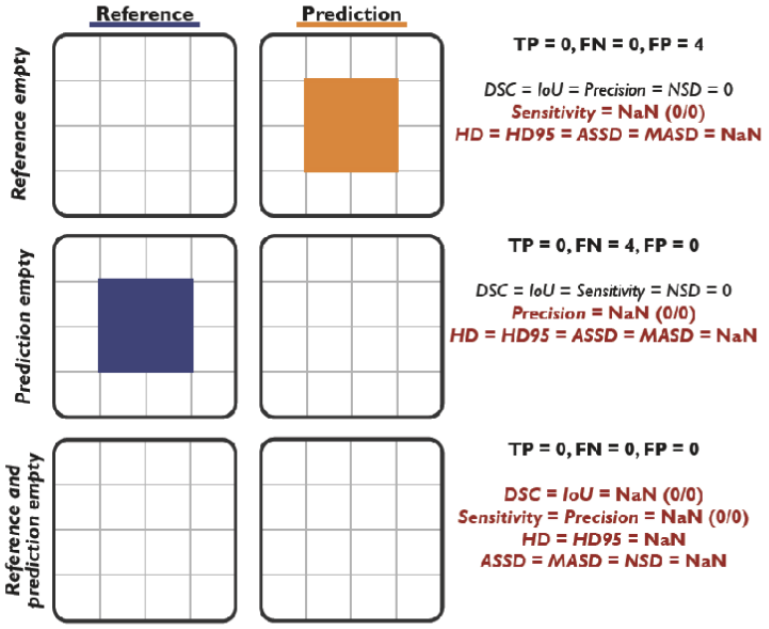


Figure 11: Extended Data Fig. SN 2.6 [2]

3.4.5 Effect of Annotation noise



3.4.6 Effect of empty labelmaps



3.4.7 Effect of resolution

Differences in the grid size (resolution) of an image highly influence the image and the reference annotation (dark blue shape (reference) vs. pink outline (desired circle shape)), with a prediction of the exact same shape leading to different metric scores.

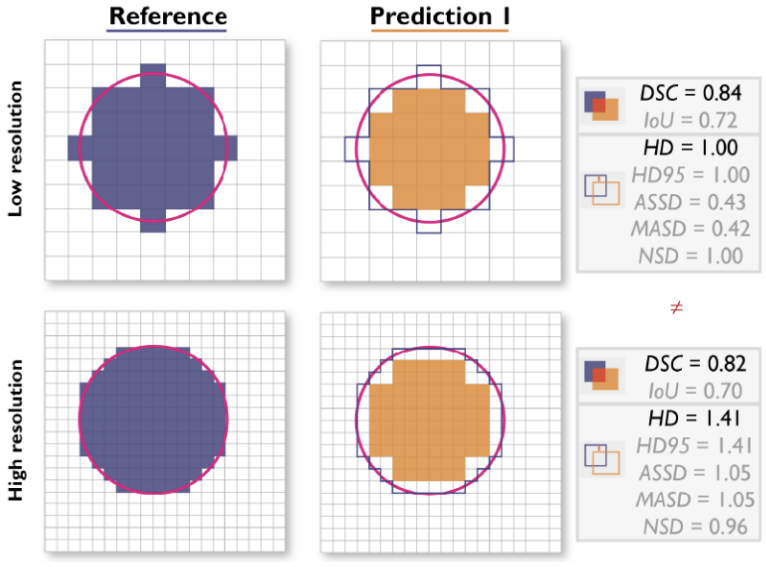


Figure 12: Effect of different grid sizes. Extended Data Fig. SN 2.36 [2]

3.5 Preference for oversegmentatin to undersegmentation

The outlines of the predictions of two algorithms (Prediction 1/2) differ in only a single layer of pixels (Prediction 1: undersegmentation — smaller structure compared to eference, Prediction 2: oversegmentation — larger structure compared to reference).

If penalizing of either over- or undersegmentation is desired (unequal severity of class confusions),

other metrics such as the F_β Score provide specific penalties for either depending on the chosen hyperparameter β. This pitfall is also relevant for other overlap-based metrics such as centerline Dice Similarity Coefficient (clDice)

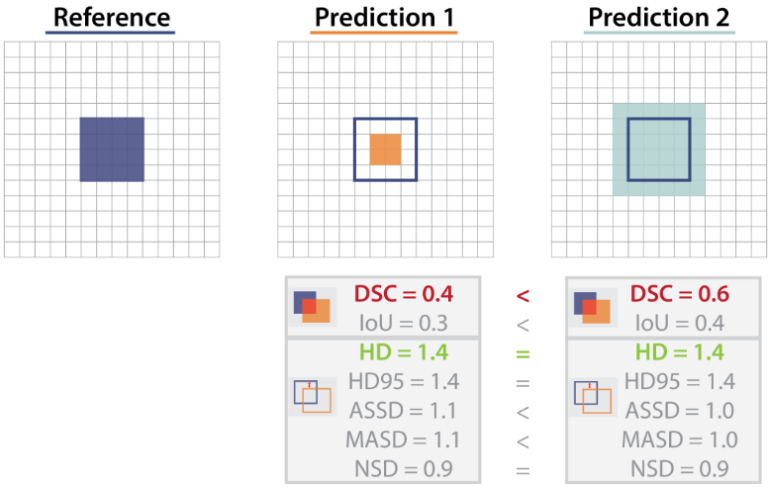
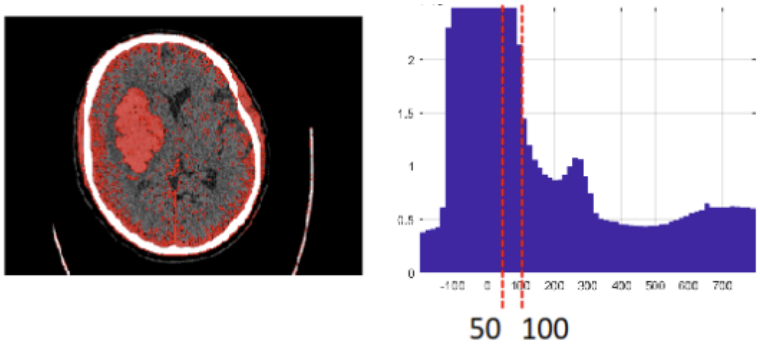


Figure 13: Extended Data Fig. SN 2.10 [2]

4 Segmentation Methods

4.1 Intensity-based segmentation — thresholding

By generating a histogram of values from a scan, you can choose which pixels to keep based on a threshold. When one threshold doesn't work initially, you can use multiple thresholds with upper and lower thresholds



4.1.1 Advantages

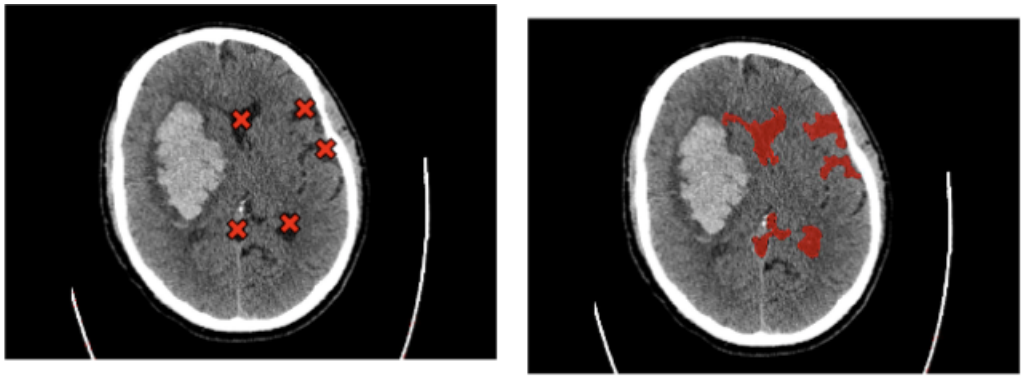
Simple and fast

4.1.2 Disadvantages

- regions must be homogeneous and distinct
- difficulty in finding consistent thresholds across images
- leakages, isolated pixels and 'rough' boundaries likely

4.2 Region-based — region growing

Start from (user selected) seed point(s) and grow a region according to an intensity threshold.



4.2.1 Advantages

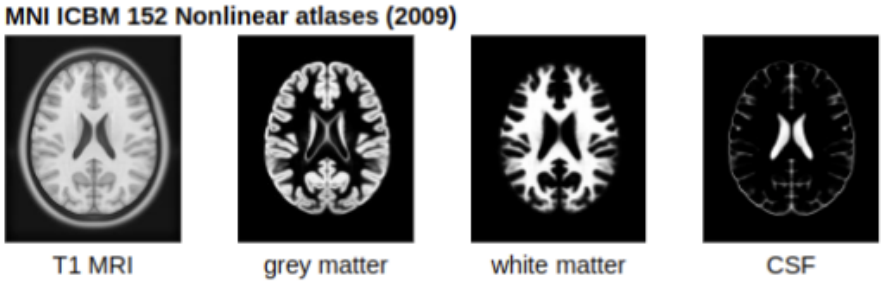
relatively fast and yields connected regions (From a seed point)

4.2.2 Disadvantages

- regions must be homogeneous
- leakages and 'rough' boundaries likely
- requires (user) input for seed points

4.3 Atlas-based segmentation

An atlas is some kind of prototype or examplar of the anatomy that we want to segment, or a template of the obejct we would like to segment.



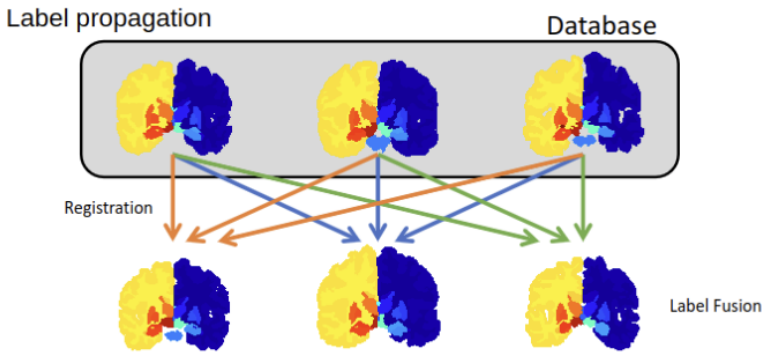
Atlases usually have geometric informatino about points, curves or surfaces, or label information about voxels (Anatomical regions or function). Atlases are usually constructed from example data: single subjects or populations of subjects e.g. by averaging to produce probabilistic atlases.

The image above isn't a specific patient, but it is a statistical population average with probability maps for were brain matter is. We can use these as priors to segment other patients.

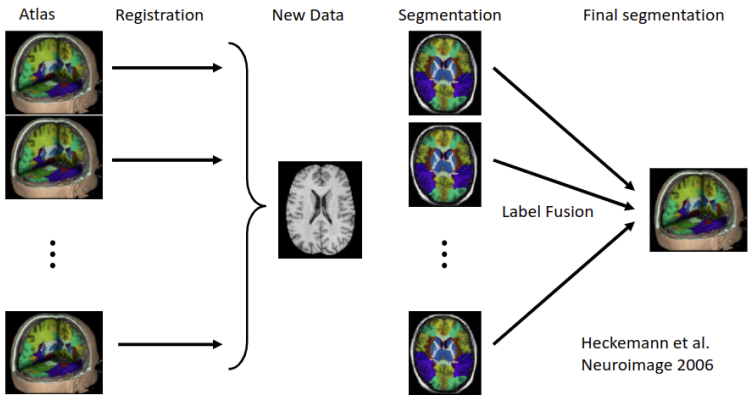
4.4 Segmentation using Registration

Uses atlases to mutate and trasnform existing segmented images (or atlases) to form the same properties as the image you're trying to segment now. By using more than one image, the target image now

has multiple predictions of the segmentation, and a lable fusion must occur.



4.5 Multi-Atlas Label Propagation



Upon fusion, it is possible to keep a probability distirbution to indicate that there was contention between different sources.

4.5.1 Advantages

- robust and accurate (like ensembles)
- yields plausible segmentations
- fully automatic

4.5.2 Disadvantages

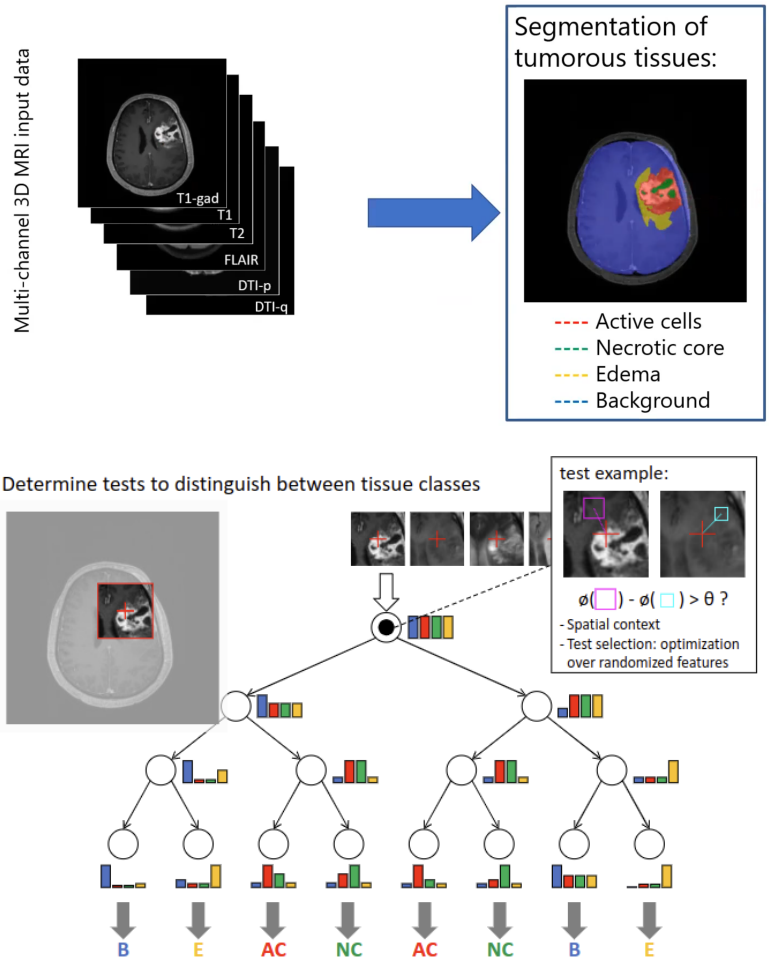
- computationally expensive
- cannot deal well with abnormalities
- not suitable for tumour segmentation

4.6 Learning-based segmentation — random forests, convolutional neural networks

4.6.1 Random forests

Begin by taking different 3D views or obtain multiple contrasts of the same anatomy but in a different way (based on differen physical scans) of the same target. Afterwards, combine them into a 4D tensor, and predict a segmentaiton of the tumorous tissues. It is great because all pateints are different.

At each branch, decide a splitting criteria that will give you the best possible split amongs the data. At training, the tree tries to cluster classes together.



paper1 and paper2

4.6.2 Advantages

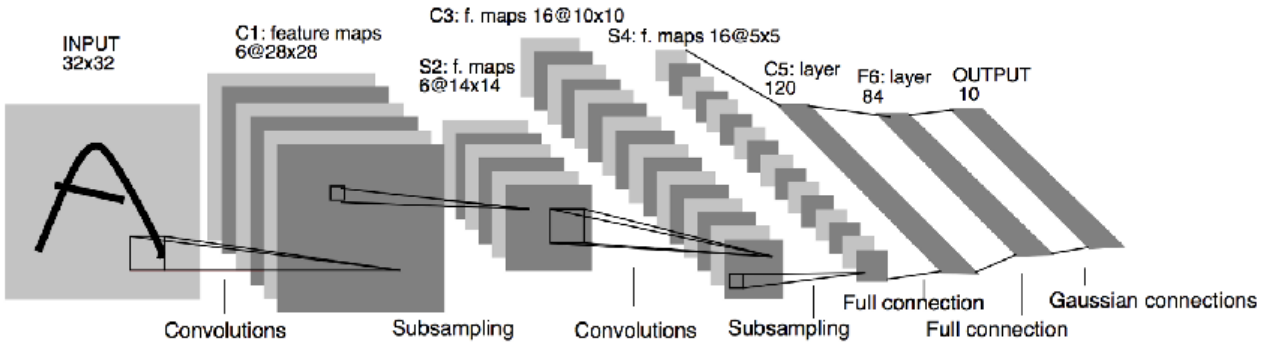
- ensemble classifiers are robust and accurate
- computationally efficient (can run in parallel)
- fully automatic

4.6.3 Disadvantages

- shallow model, no hierarchical features
- no guarantees on connectedness

5 Segmentation via Dense Classification

5.1 LeNet




```python
# from https://pytorch.org/tutorials/beginner/blitz/neural_networks_tutorial.html
# https://www.analyticsvidhya.com/blog/2023/11/lenet-architectural-insights-and-practical-implementation/
import torch
import torch.nn as nn
import torch.nn.functional as F


class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 5x5 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, kernel_size=5)
        self.pool1 = nn.AvgPool2d(2, stride=2)
        self.conv2 = nn.Conv2d(6, 16, kernel_size=5)
        self.pool2 = nn.AvgPool2d(2, stride=2)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.pool1(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = self.pool2(x)

        x.torch.flatten(x,1) # flatten all dimensions except the batch dimension

        x = self.fc1(x)
        x = F.relu(x)
        x = self.fc2(x)
        x = F.relu(x)
        x = self.fc3(x)

        return x
```

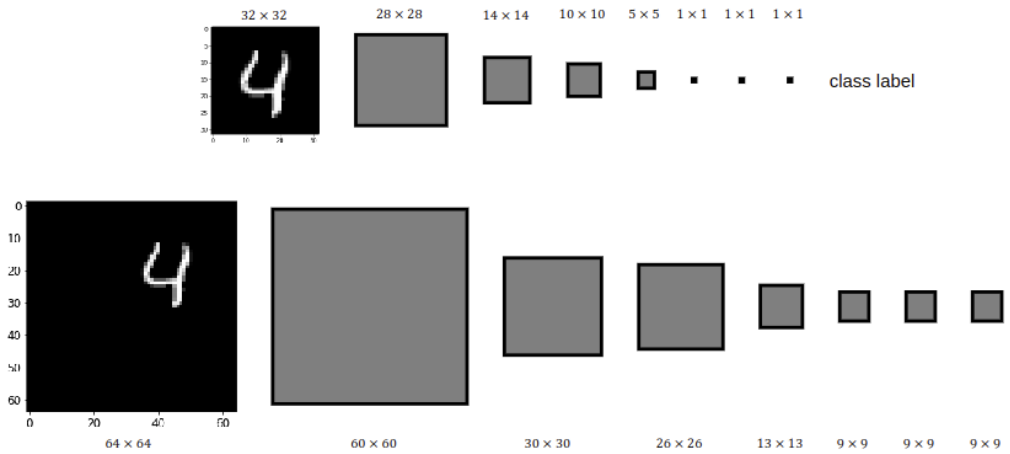
code/LeNet.py

5.1.1 Fully convolutional LeNet

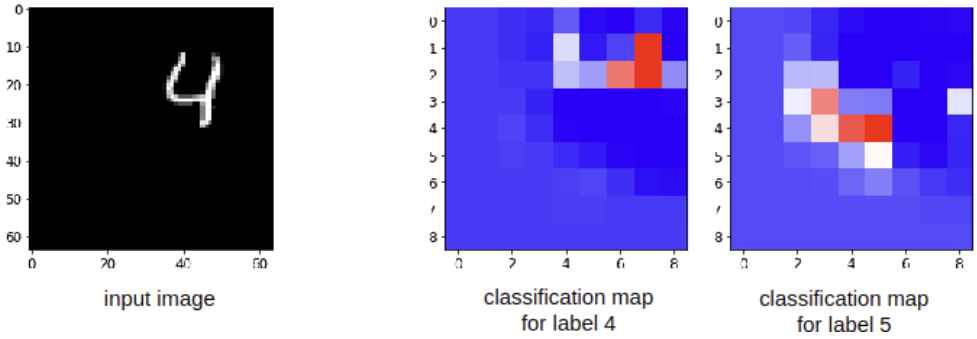
Pay attention to line 19 onwards. If we wanted to translate the network into a fully convolutional LeNet:

```
1  import torch
2  import torch.nn as nn
3  import torch.nn.functional as F
4
5
6  class Net(nn.Module):
7
8      def __init__(self):
9          super(Net, self).__init__()
10         # 1 input image channel, 6 output channels, 5x5 square convolution
11         # kernel
12         self.conv1 = nn.Conv2d(1, 6, kernel_size=5)
13         self.pool1 = nn.AvgPool2d(2, stride=2)
14         self.conv2 = nn.Conv2d(6, 16, kernel_size=5)
15         self.pool2 = nn.AvgPool2d(2, stride=2)
16         self.conv3 = nn.Conv2d(16, 120, kernel_size=5) # changed
17         self.conv4 = nn.Conv2d(120, 84, kernel_size=1) # changed
18         self.conv5 = nn.Conv2d(84, 10, kernel_size=1)  # changed
19
20     def forward(self, x):
21         x = self.conv1(x)
22         x = F.relu(x)
23         x = self.pool1(x)
24         x = self.conv2(x)
25         x = F.relu(x)
26         x = self.pool2(x)
27
28         x = self.conv3(x)
29         x = F.relu(x)
30         x = self.conv4(x)
31         x = F.relu(x)
32         x = self.conv5
33
34         return F.log_softmax(x, dim=1)
```

code/LeNet–fullyconnected.py

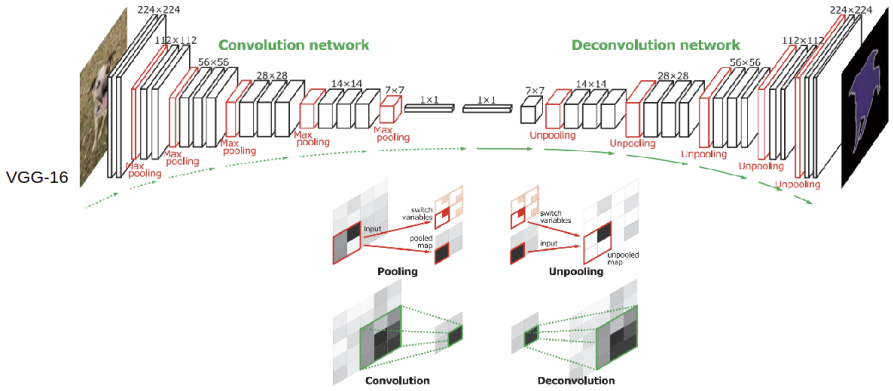


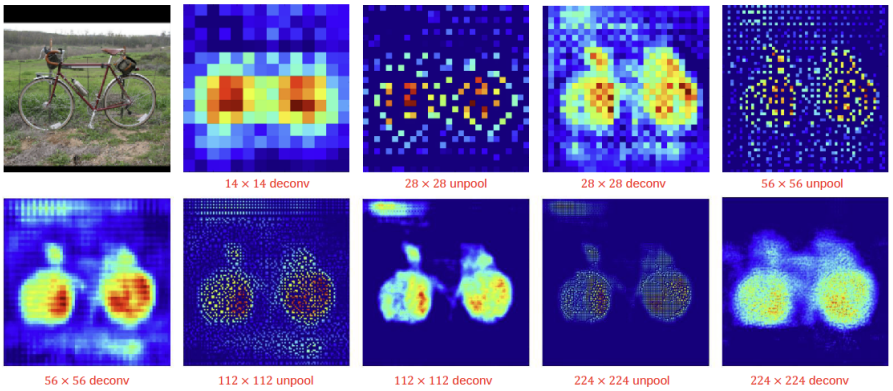
We go beyond classification. If we're given a 64x64 image, at the end of the network, we get an output feature-map.



The classication maps can be used to localise where it is, and that there is a number there (a 4). The 5, is garbage becuase there is a 5. This input is scaled up through up-sampling (Section 6.1.1)

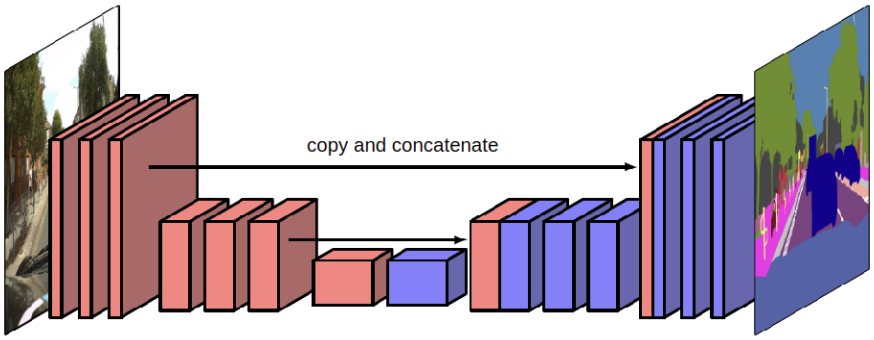
6 Encoder-Decoder Networks



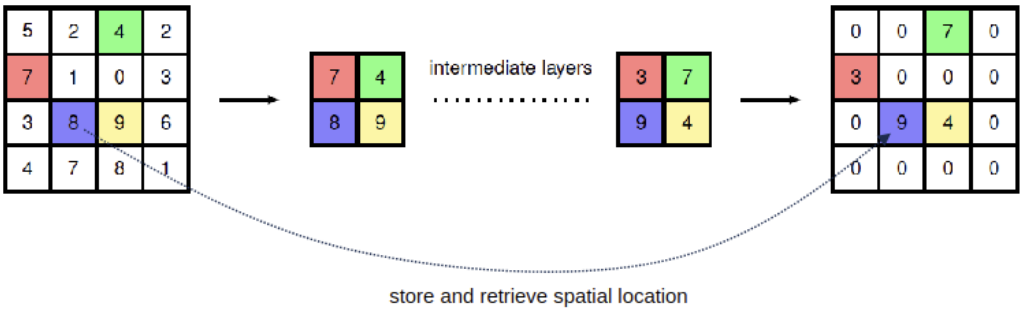


The idea is to take a really low level representation of an image and try to upsample it back to its original resolution. This is what the U-Net is trying to achieve.

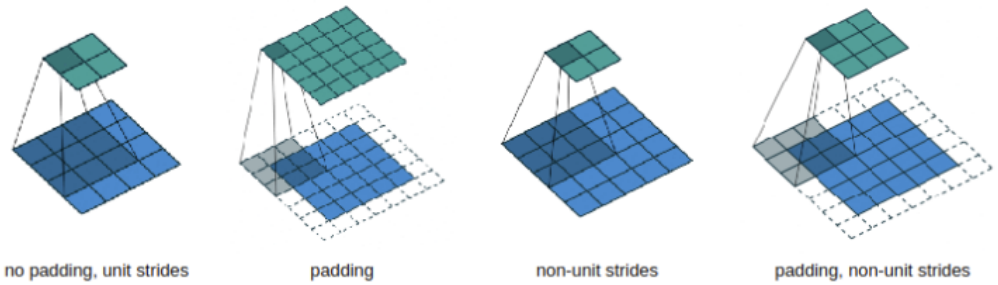
6.1 U-Net



6.1.1 Upsampling

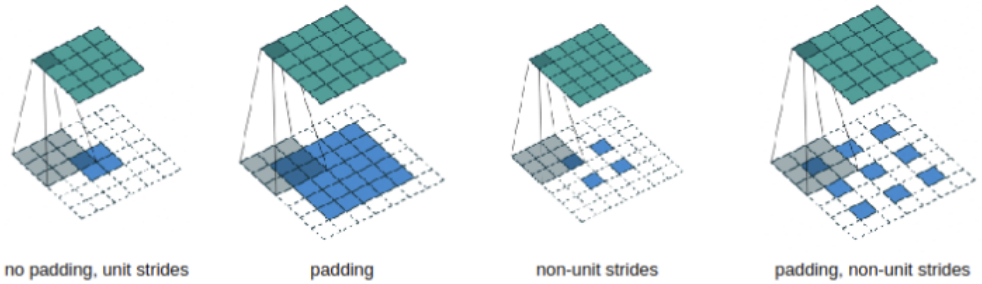


6.1.2 Convolutions



link

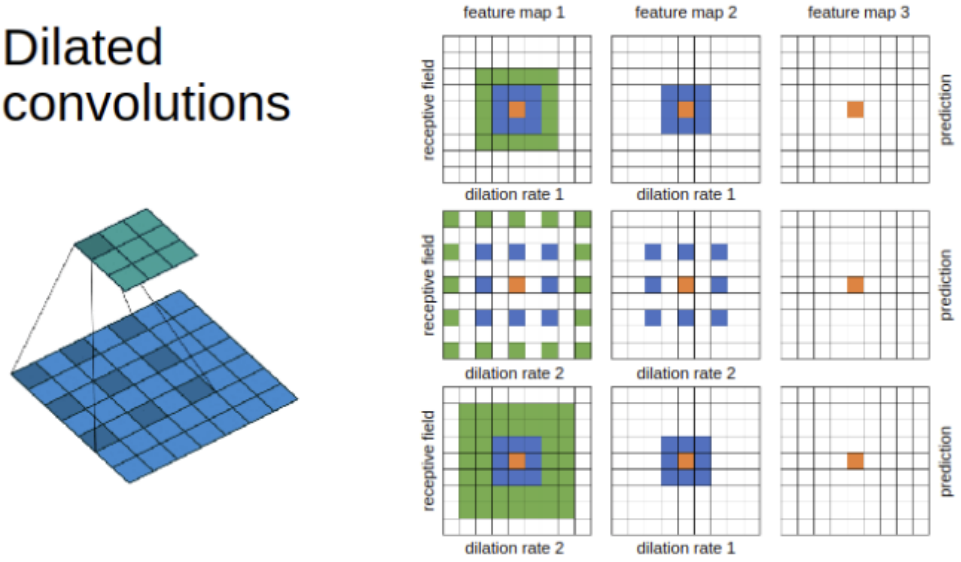
6.1.3 Transpose convolutions



Transpose convolutions can be used for 'learned' up-sampling

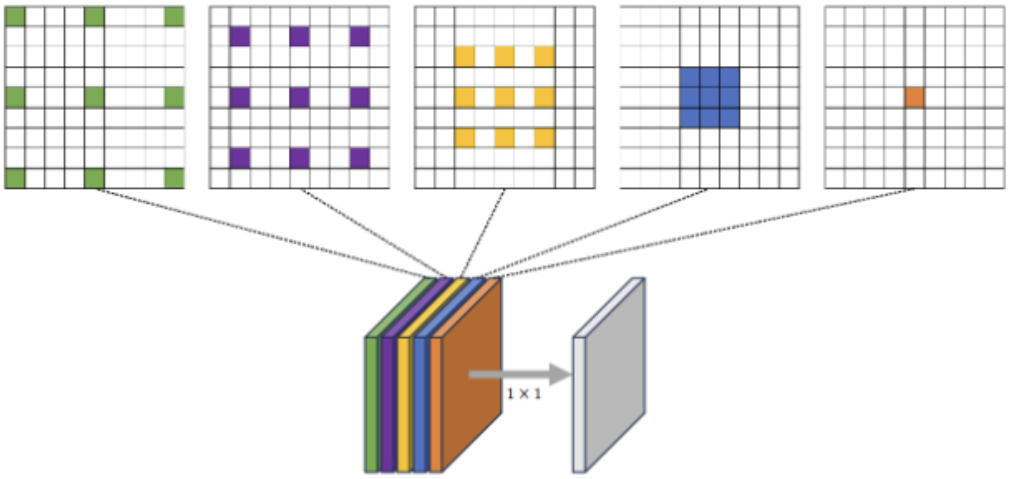
link

6.1.4 Dilated convolutions



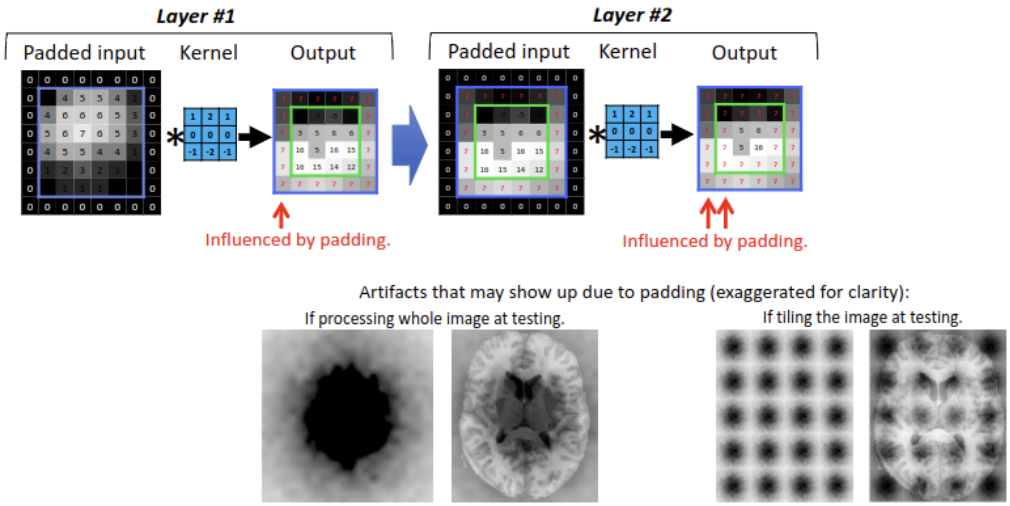
link

6.1.5 Atrous spatial pyramid pooling



link

6.1.6 Padding effects

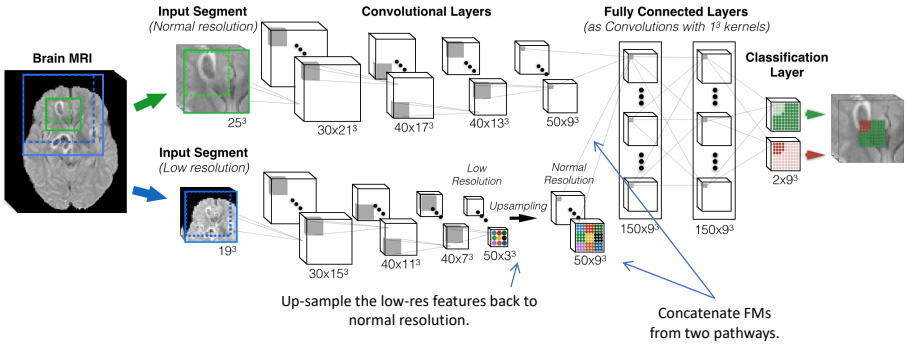


the padding may propogate values in the features, or if we used tiling or sliding window appraoch, we may get a repeating pattern.

6.1.7 Multi-scale processing

Multi-scale processing

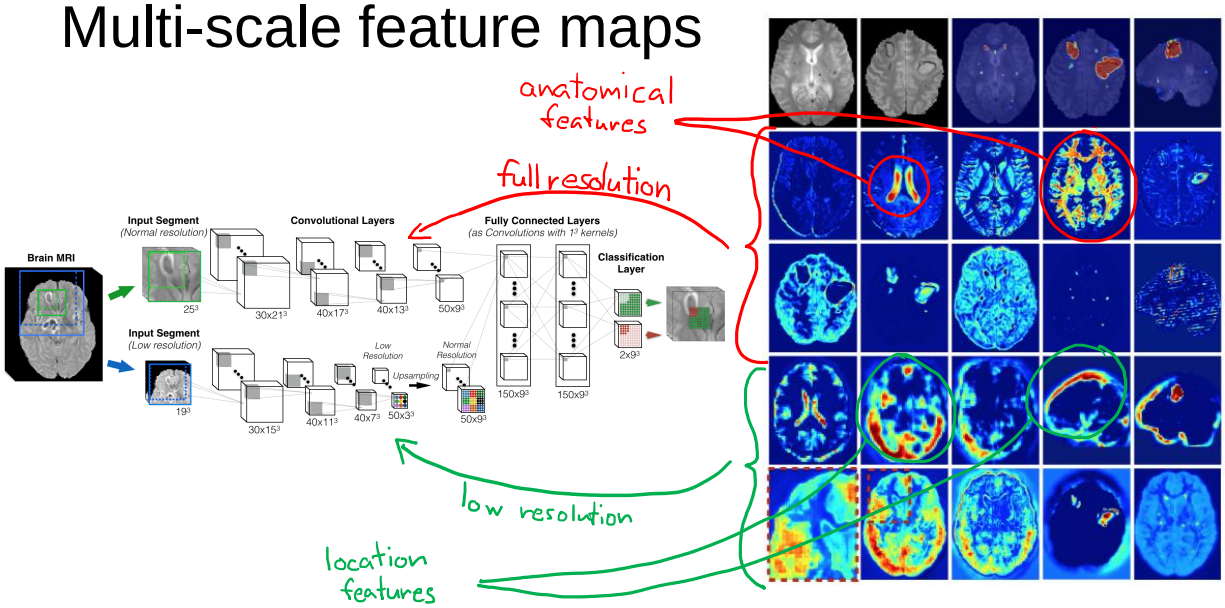
- What else can we do to make the network “seeing” more context?
- **Idea:** Add pathways which process down-sampled images



Kamnitsas et al. 2017. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation 129

the idea of not using a decoder that given an input patch, we process it (without maxpooling) by applying convolutional layers and then we have the kernel of fully connected layers. Here, we have a receptive field, i.e. how much information we can see. The solution here is to take another network and process in paralell, the iamge at a lower resolution. Here we can see more spatial context.

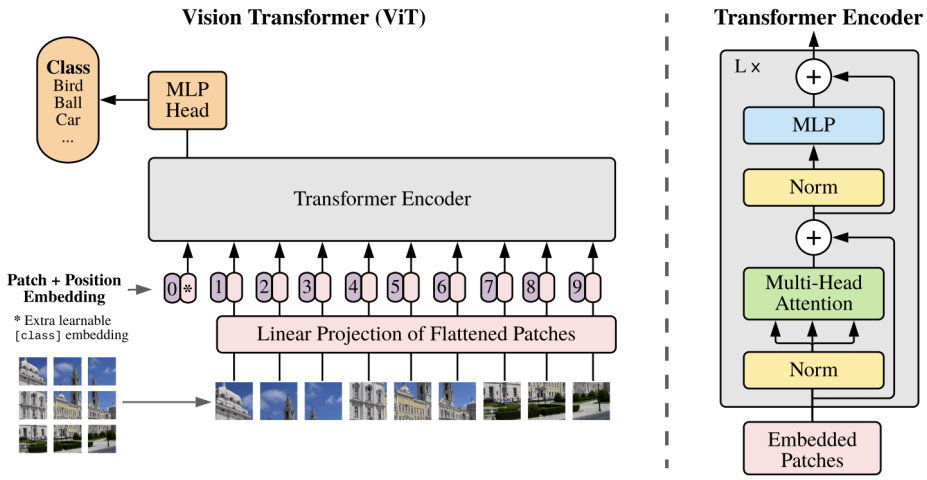
Multi-scale feature maps



Kamnitsas et al. 2017. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation 130

6.2 Vision trasnformers

Vision transformers



Dosovitskiy et al. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

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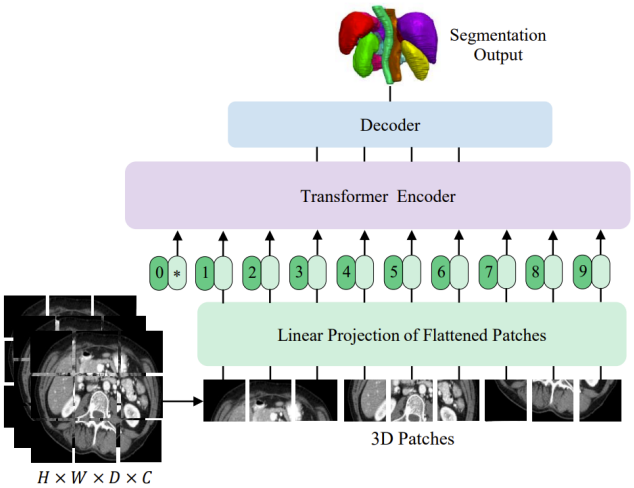
Transformers for image segmentation



Hatamizadeh et al. 2021. UNETR: Transformers for 3D Medical Image Segmentation

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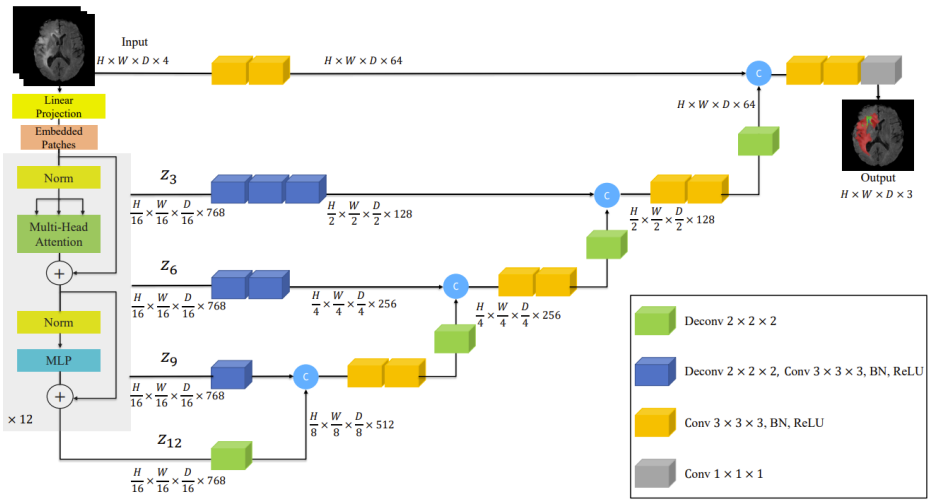
Transformers for image segmentation



Hatamizadeh et al. 2021. [UNETR: Transformers for 3D Medical Image Segmentation]

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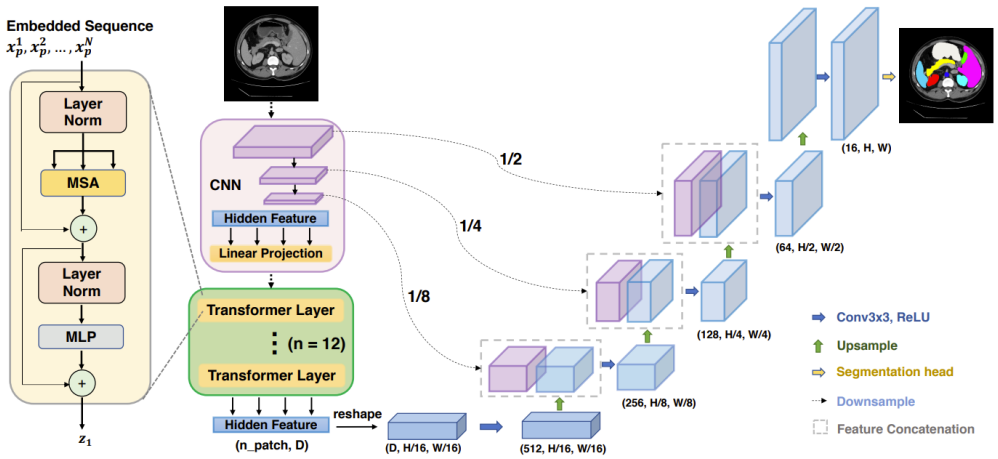
Transformers for image segmentation



Chen et al. 2021. [TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation]

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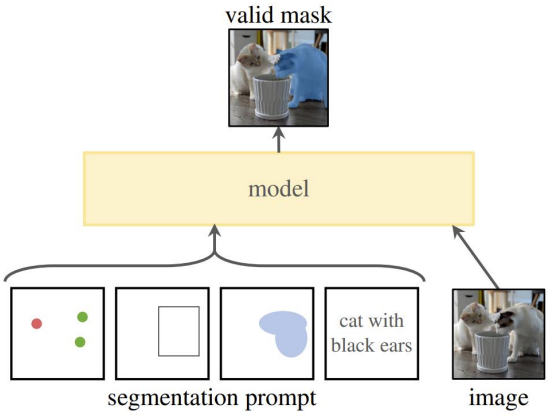
Transformers for image segmentation



Kirillov et al. 2023. Segment Anything

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[1] Alexey Dosovitskiy et al. *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale*. 2020. arXiv: 2010.11929 [cs.CV].

[2] Annika Reinke et al. *Understanding metric-related pitfalls in image analysis validation*. 2023. arXiv: 2302.01790 [cs.CV].