



DEEPHEALTH

Use Case 12

Lab 2: Skin Lesion Segmentation

Winter School 25/01/2022

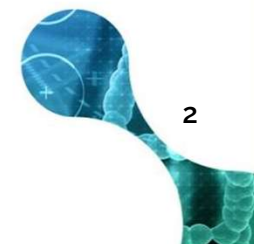


The project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 825111.



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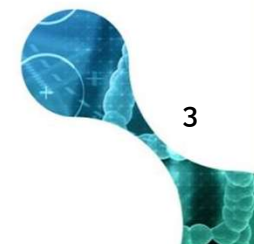


Skin Lesion Image Analysis

Introduction



- Skin cancer is a major public health issue, with malignant melanoma being the deadliest form of it and presenting millions of newly diagnosed cases every year.
- Dermoscopy is an imaging technique that eliminates the surface reflection of skin. By removing surface reflection, visualization of deeper levels of skin is enhanced.
- When used by expert dermatologists, dermoscopy provides improved diagnostic accuracy, in comparison to standard photography.



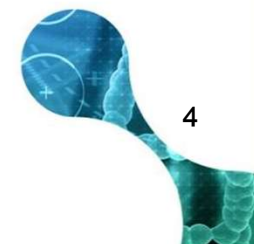


ISIC

International Skin Imaging Collaboration



- The International Skin Imaging Collaboration (ISIC) contains the largest publicly available collection of quality controlled dermoscopic images of skin lesions.
- Collected from leading clinical centers internationally and acquired from a variety of devices within each center.
- Since 2016, ISIC has sponsored annual challenges for the computer science community



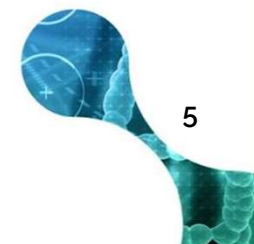


ISIC 2017 Challenge

- Purpose of the challenge: develop image analysis tools to enable the automated diagnosis of melanoma from dermoscopic images.



- Part 1: Lesion Segmentation
 - Part 2: Detection and Localization of Visual Dermoscopic Features/Patterns
 - Part 3: Disease Classification
- Segmentation is defined as the recognition of the set of pixels that constitute the skin lesion within the image. It is employed in 2017 and 2018 challenges.
 - The 2017 challenge was chosen because for the 2018 challenge test ground truth are still not provided.



Dataset

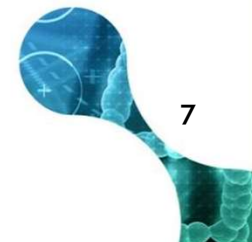


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Segmentation Dataset

- Goal: automated predictions of lesion segmentation boundaries from dermoscopic images, in the form of a binary mask (0 background, 255 foreground).



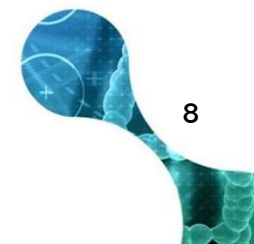


Segmentation Dataset

Data description

- Images are in .jpg format, while masks in .png format.
- Each image has only one lesion within it
- Dimensions of the images: from 576x768 to 6748x4439

Split	Number of images
Training	2000
Validation	150
Test	600



Models

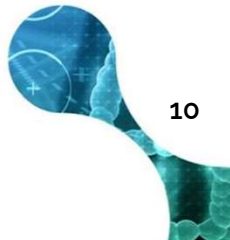
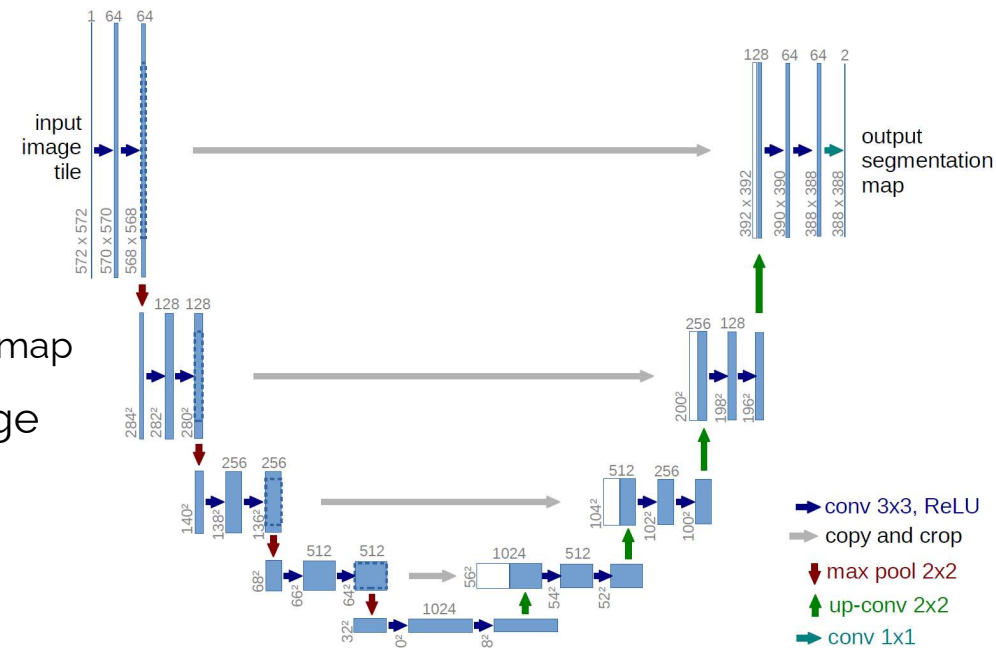


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UNet

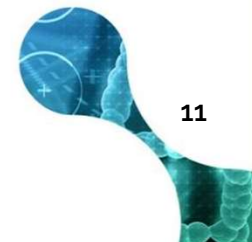
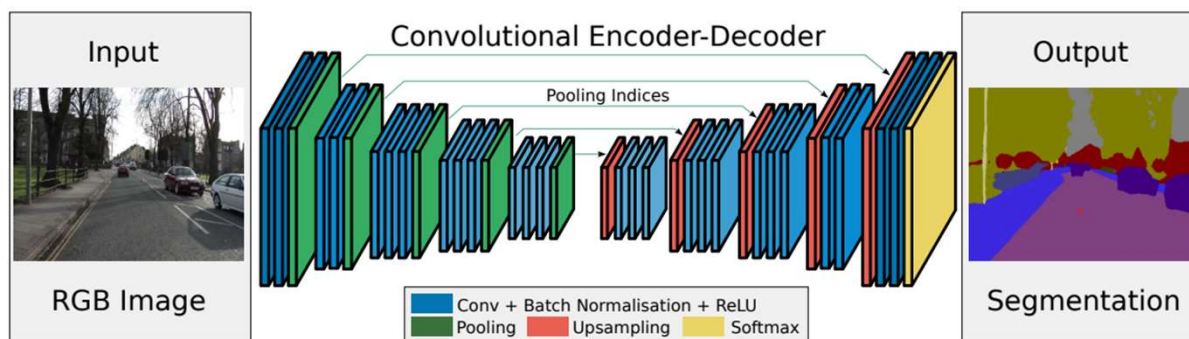
- Standard approach: encoder-decoder convolutional neural network.
 - Encoder: increase the “what” and reduce the “where”
 - Decoder: create high-resolution segmentation map
- **UNet**, created specifically for biomedical image segmentation.
- Upsampling convolutions concatenate with features from contracting path
- Several modified UNet over the years, for example adding batch normalization and scaling the output segmentation map with the same resolution of the input.





SegNet

- Same approach: encoder-decoder convolutional neural network.
 - Encoder: VGG16, with pooling layers that memorize the locations of the maximum feature value in each pooling window for each encoder feature map.
 - Decoder: for each encoder layer, there exists a corresponding decoder layer to upsample the feature maps to its original size, which uses the memorized max-pooling indices from the corresponding encoder feature map. In this way, SegNet uses less memory compared to UNet, which concatenate the entire feature map from the encoder.
- Actually, EDDL for now didn't retrieve the pooling indices, so the upsample is just a resize of the image



Metric

- Metric: Jaccard index (Intersection over Union)
 - Quantify the percent overlap between the target mask and our prediction output
 - Number of pixels common between the target and prediction masks divided by the total number of pixels present across both masks.

$$IoU = \frac{|target \cap prediction|}{|target \cup prediction|} = \frac{|target \cap prediction|}{|target| + |prediction| - |target \cap prediction|}$$

- This metric is closely related to the Dice coefficient which is often used as a loss function during training.

$$Dice\ coefficient = \frac{2 |target \cap prediction|}{|target| + |prediction|}$$

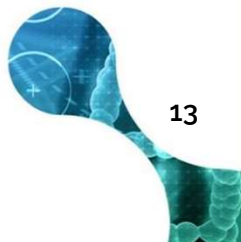
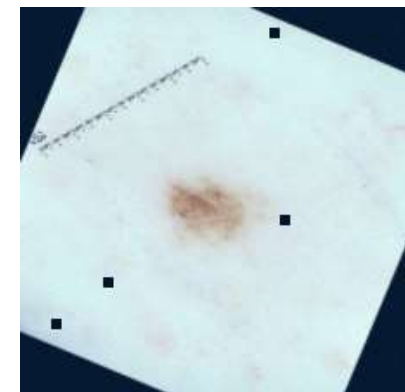
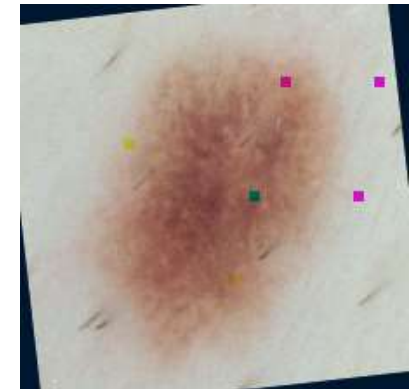
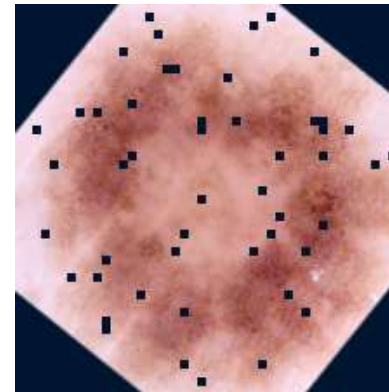




Pre Processing

- Pre processing consists in several data augmentation functions:

```
training_augs = ecv1.SequentialAugmentationContainer([
    ecv1.AugResizeDim(image_size, ecv1.InterpolationType.cubic,
        gt_interp=ecv1.InterpolationType.nearest),
    ecv1.AugMirror(.5),
    ecv1.AugFlip(.5),
    ecv1.AugRotate([-180, 180]),
    ecv1.AugAdditivePoissonNoise([0, 10]),
    ecv1.AugGammaContrast([0.5, 1.5]),
    ecv1.AugGaussianBlur([0, 0.8]),
    ecv1.AugCoarseDropout([0, 0.03], [0.02, 0.05], 0.25),
    ecv1.AugToFloat32(255, divisor_gt=255),
    ecv1.AugNormalize([0.6681, 0.5301, 0.5247],
        [0.1337, 0.1480, 0.1595]), # isic stats
])
```

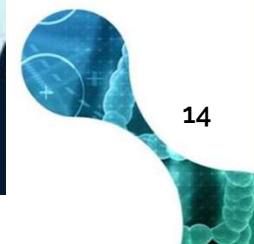
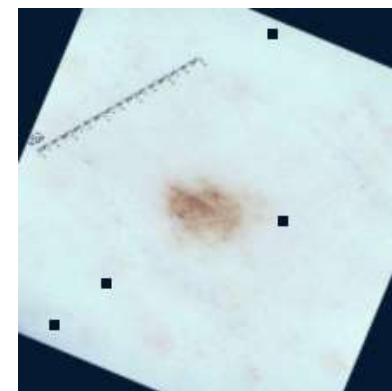
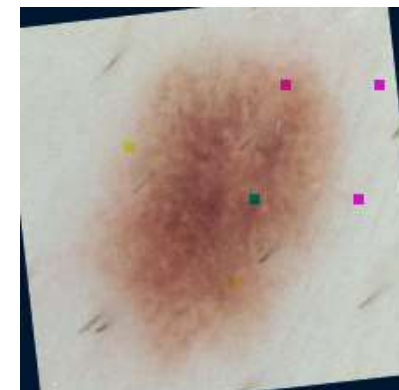
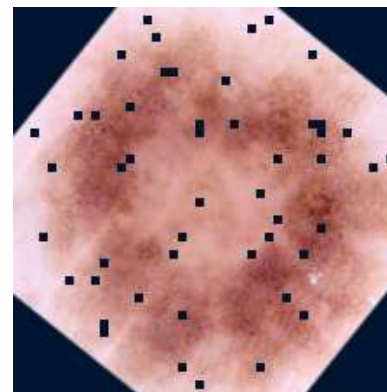




Pre Processing

- Or in ECVL Augmentation Language:

```
SequentialAugmentationContainer
  AugResizeDim dims=(512,512) interp="cubic" gt_interp="nearest"
  AugMirror p=0.5
  AugFlip p=0.5
  AugRotate angle=[-180, 180]
  AugAdditivePoissonNoise lambda=[0, 10]
  AugGammaContrast gamma=[0.5, 1.5]
  AugGaussianBlur sigma=[0, 0.8]
  AugCoarseDropout p=[0, 0.03] drop_size=[0.02, 0.05] per_channel=0.25
  AugToFloat32 divisor=255 divisor_gt=255
  AugNormalize mean=(0.6681, 0.5301, 0.5247) std=(0.1337, 0.1480, 0.1595)
end
```

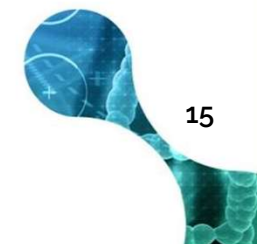




Post Processing

- To qualitatively evaluate the results, when the output of the neural network is saved, a little of post processing is added.
- *ConnectedComponentsLabeling* finds the connected components of the predicted mask
- Their contours are then colored red on the original image

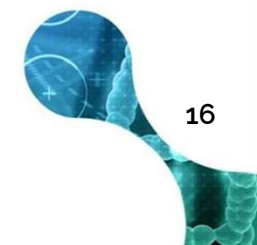
```
tmp, labels = ecvl.Image.empty(), ecvl.Image.empty()
ecvl.ConvertTo(img_t, tmp, ecvl.DataType.uint8)
ecvl.ConnectedComponentsLabeling(tmp, labels)
ecvl.ConvertTo(labels, tmp, ecvl.DataType.uint8)
contours = ecvl.FindContours(tmp)
ecvl.ConvertTo(orig_img_t, tmp, ecvl.DataType.uint8)
tmp_np = np.array(tmp, copy=False)
for cseq in contours:
    for c in cseq:
        tmp_np[c[0], c[1], 0] = 255
        tmp_np[c[0], c[1], 1] = 0
        tmp_np[c[0], c[1], 2] = 0
```





Results

Model	Loss	Optimizer	Initial LR	Epochs	Best epoch	Validation IoU	Test IoU
SegNet	Binary Cross Entropy	Adam	1e-5	100	49	0.725	0.708
SegNetBN	Binary Cross Entropy	Adam	1e-5	100	99	0.745	0.714
Unet	Binary Cross Entropy	Adam	1e-5	100	46	0.755	0.718
Unet	Dice	Adam	1e-3	100	74	0.750	0.733



Resources



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Resources

Original Dataset

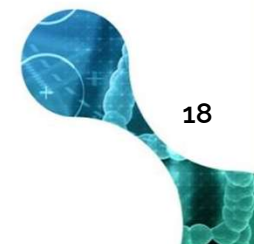
[ISIC Challenge Datasets](#)

Prepared Dataset

isic_segmentation.zip (11,3 GB) [Option 1](#) [Option 2](#)

Pipeline Repository

[UC12_pipeline](#)
[use-case-pipelines](#)





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Thank you!

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