UNIVERSIDAD NACIONAL AUTÓNOMA DE MÉXICO

Posgrado en Ciencia e Ingeniería de la Computación

Curso de aprendizaje profundo

DoubleU-Net: A Deep Convolutional Neural Network for Medical Image Segmentation

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Content

Introduction
Medical image segmentation

Medical image segmentation is the task of labeling each pixel of an object of interest in medical images

Aplications

- Computer Aided Diagnosis for lesions detection
- Therapy planning and guidance

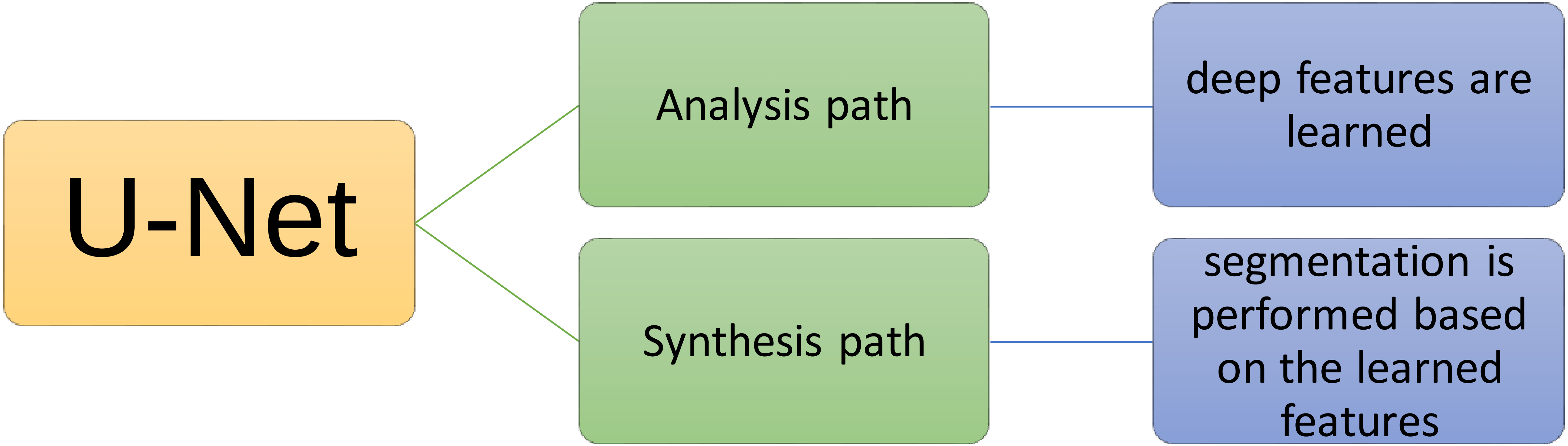
Challenges

- Unavailability of a large number of annotates
- Lack of high-quality labeled images for training
- Low image quality
- A large variations of images among patients

Introduction
Segmentation task and U-Net network

In the state-of-the-art Convolutional Neural Networks (CNNs) have shown a good performance for automated medical image segmentation.

For example: U-Net



Related work in the field of medical image segmentation

U-Net Model

U-Net have gained significant popularity among semantic segmentation approach for 2D images.

In the medical imaging, there are many challenging images, which are usually missed out during colonoscopy examination and can develop into cancer if early detection is not performed. Therefore, there is a need for a more accurate medical image segmentation approach to deal with the challenging images

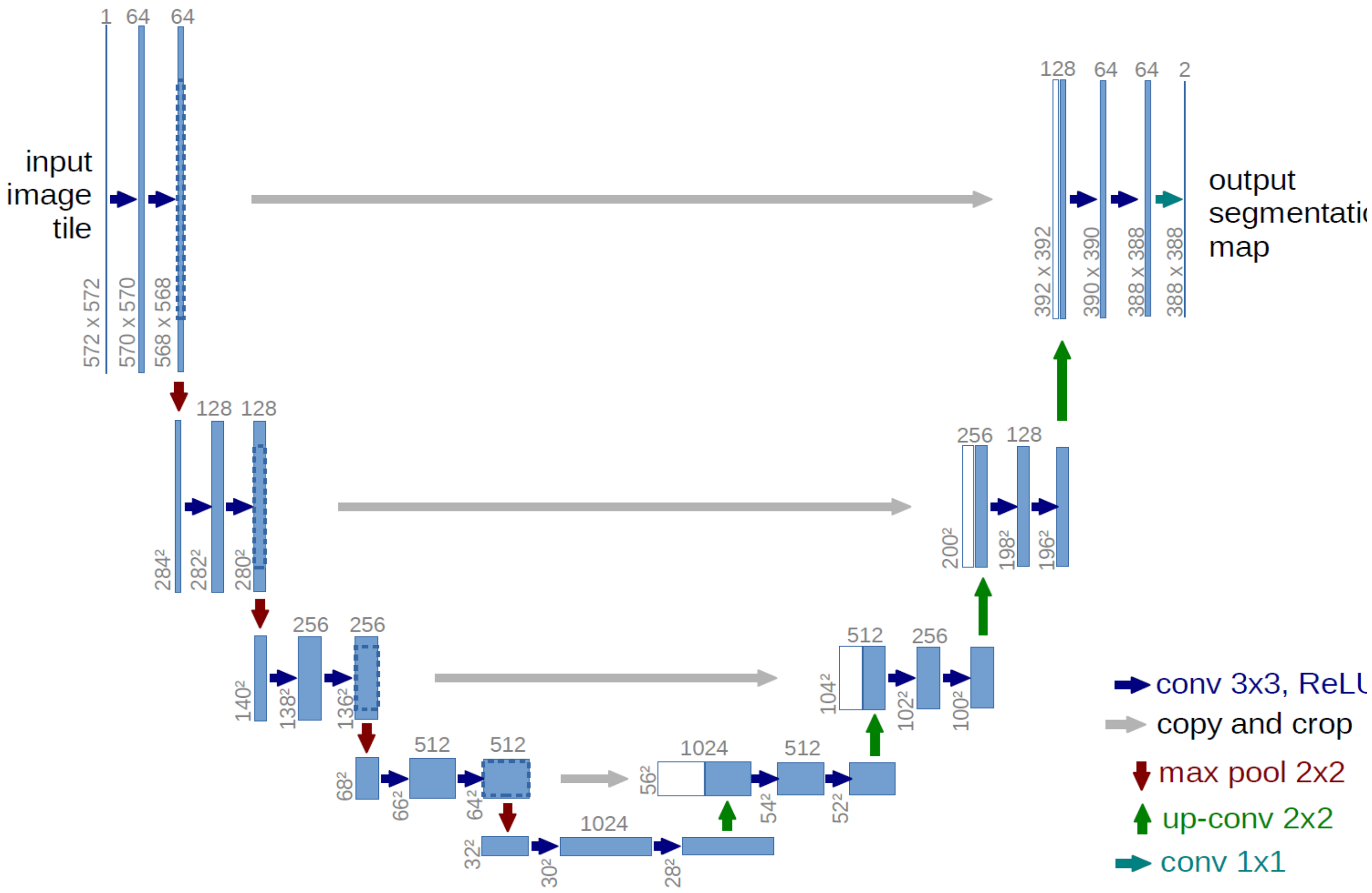
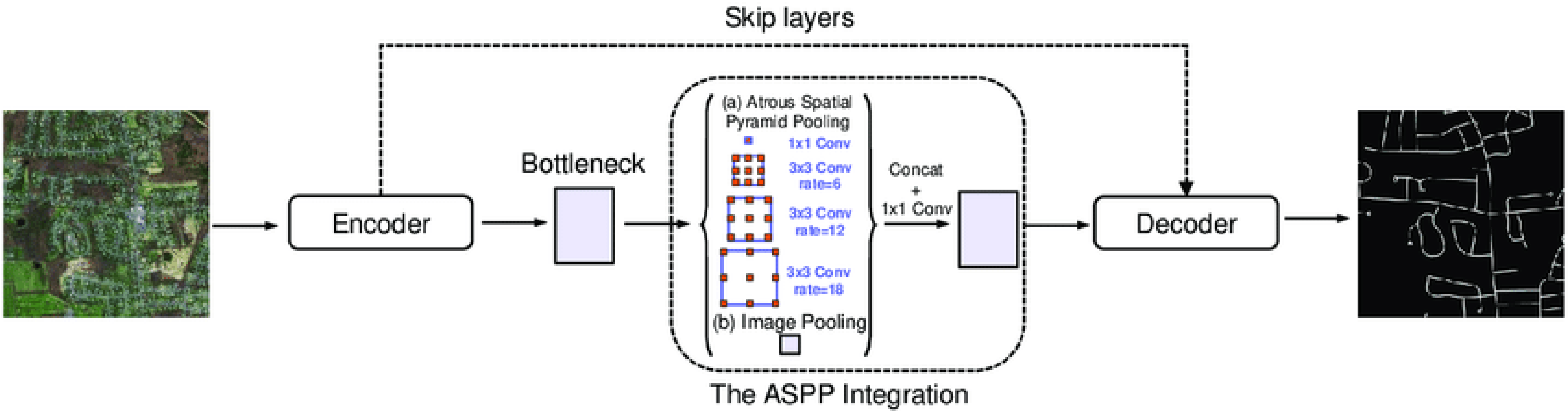


Image: https://paperswithcode.com/method/u-net



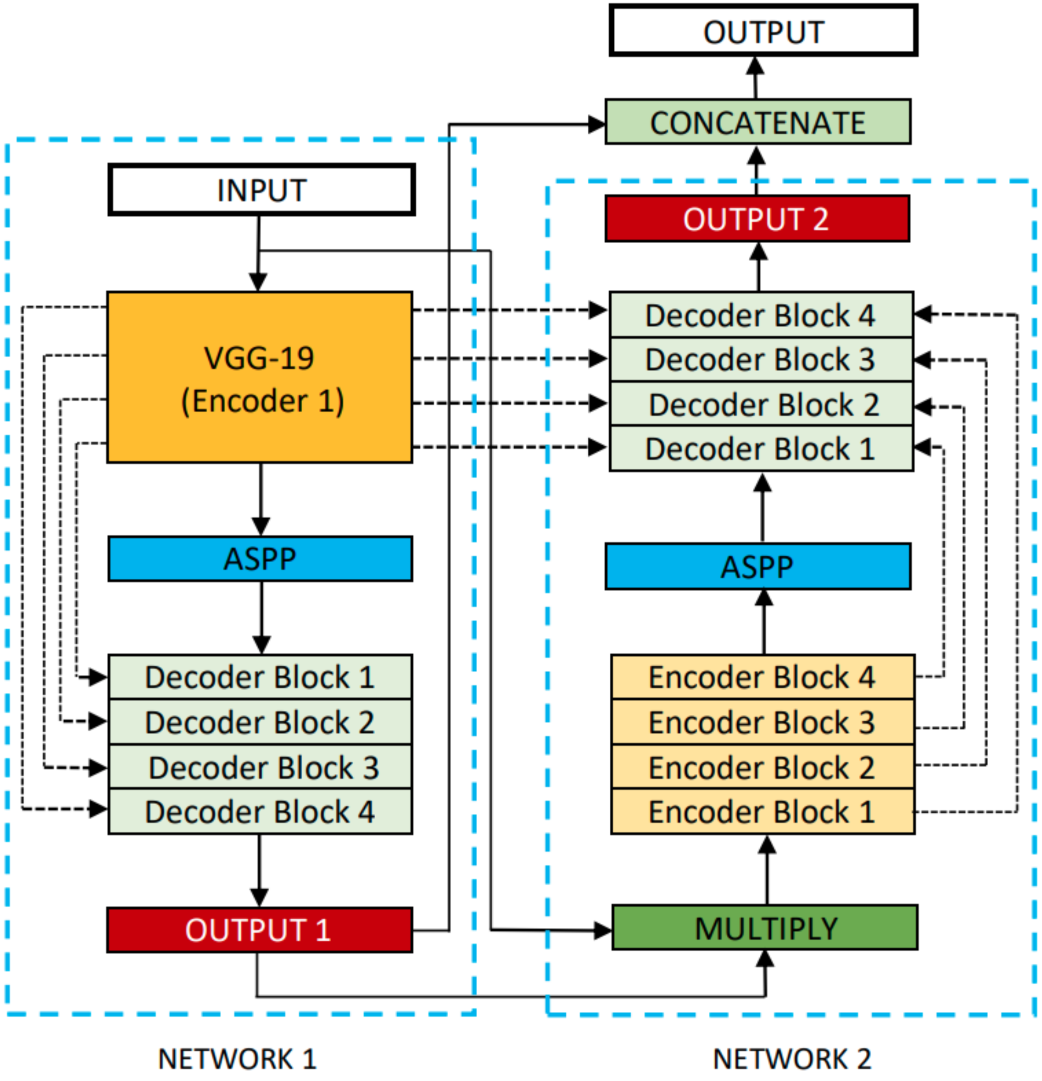
Atrous Spatial Pyramid Pooling (ASPP)

- The ASPP module is inserted after the bottleneck of the Encoder-Decoder network. This means that the feature map generated by the encoder is processed by using ASPP, and then, the result is fed into the decoder.

Image:https://www.researchgate.net/publication

Double U-Net Architecture

The produced output feature map from NETWORK 1 can and concatenating with Output2 will produce a better segmentation mask than the previous one.



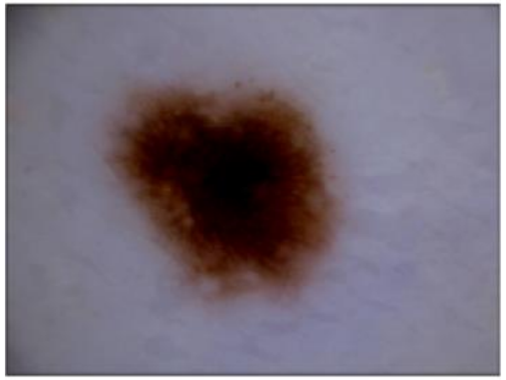
The experiments
Datasets

Dataset	Description	No. of Images	Input size	Aplication
a) 2015 MICCAI sub-challenge automatic polyp detection	It used the CVC-ClinicDB [1] for training and ETIS-Larib [2]	808	384 x 288	Colonoscopy
b) CVC-ClinicDB	For polyp segmentation	612	384 x 288	Colonoscopy
c) Lesion Boundary Segmentation dataset [3, 4]	It contains skin lesions and their corresponding annotations.	2594	Variable	Dermoscopy
d) 2018 Data Science Bowl challenge	For nuclei segmentation	670	256 x 256	Nuclei

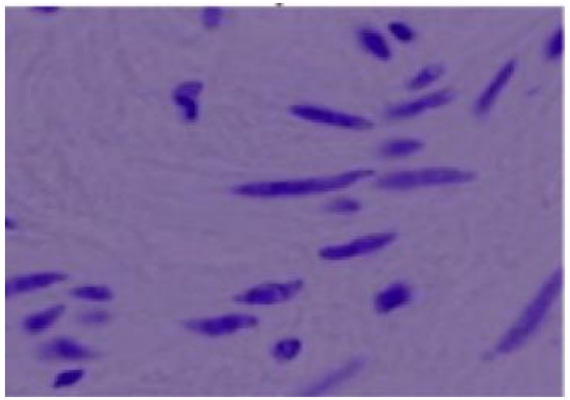
a)

b)

c)



d)



The experiments
Evaluation metrics

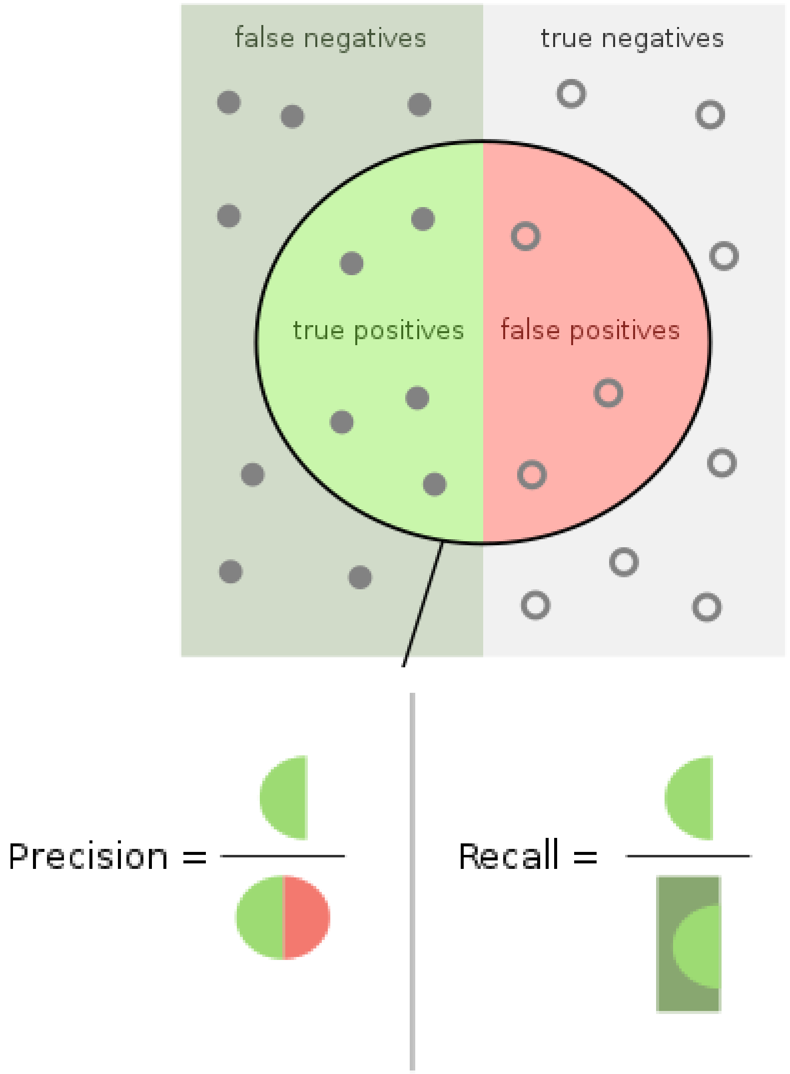
DoubleU-Net is evaluated on the basis of :

1. Precision:

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

2. Recall:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{P}} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

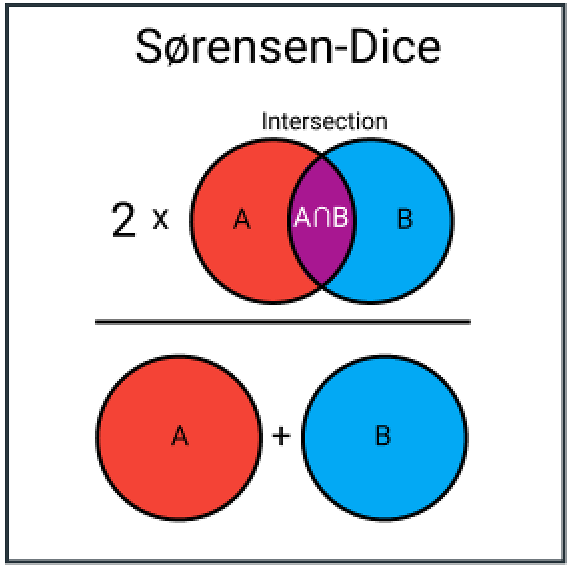


The experiments
Evaluation metrics

DoubleU-Net is evaluated on the basis of :

1. Sørensendice coefficient or Dice similarity coefficient (DSC) :

$$2\ |X \cap Y|\ /\ (|X| + |Y|)$$

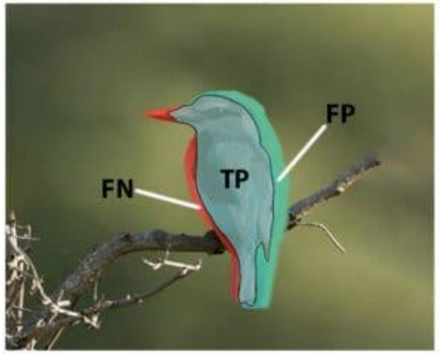


2. Mean Intersection over Union (mIoU):

$$IoU = \frac{TP}{(TP + FP + FN)}$$


Ground Truth Mask


Predicted Mask



The experiments
Experiment setup and configuration

- All models were implemented using Keras framework [5] with Tensorflow 2.1.0 [6] as backend.
- A Volta 100 GPU and an Nvidia DGX-2 AI system were used.
- In all of the datasets:

- The original image size for the smaller dataset was used and resized the images to 384×512 for the Lesion Boundary segmentation challenge dataset to balance between training time and complexity.

The experiments
Experiment setup and configuration

- Binary cross-entropy as the loss function was used.
- The Adam optimizer with its default parameters was used.
- For the lesion boundary segmentation dataset and the Nuclei segmentation dataset, the batch size was set to 16 and the learning rate to 1e−5.
- All models are trained for 300 epochs.

The experiments
Experiment setup and configuration

Different data augmentation methods to each set were applied:

- Center crop.
- Random rotation.
- Transpose.
- Elastic transform.

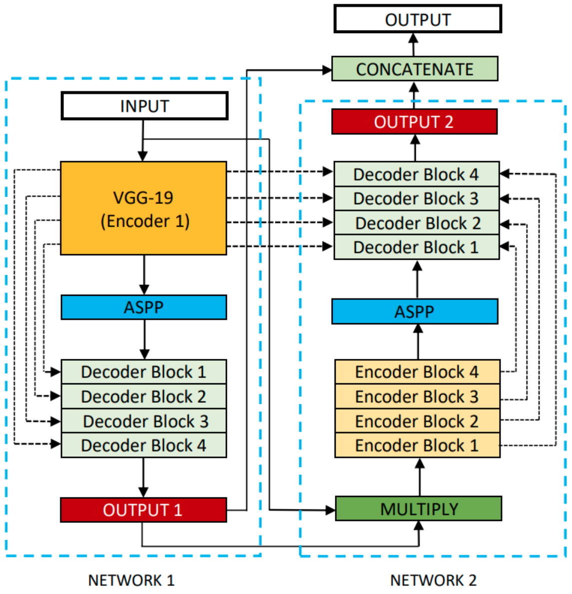
A single image was converted into 25 different images; thus, in total, 26 images including the original image. The same augmentation techniques were applied to all four datasets.

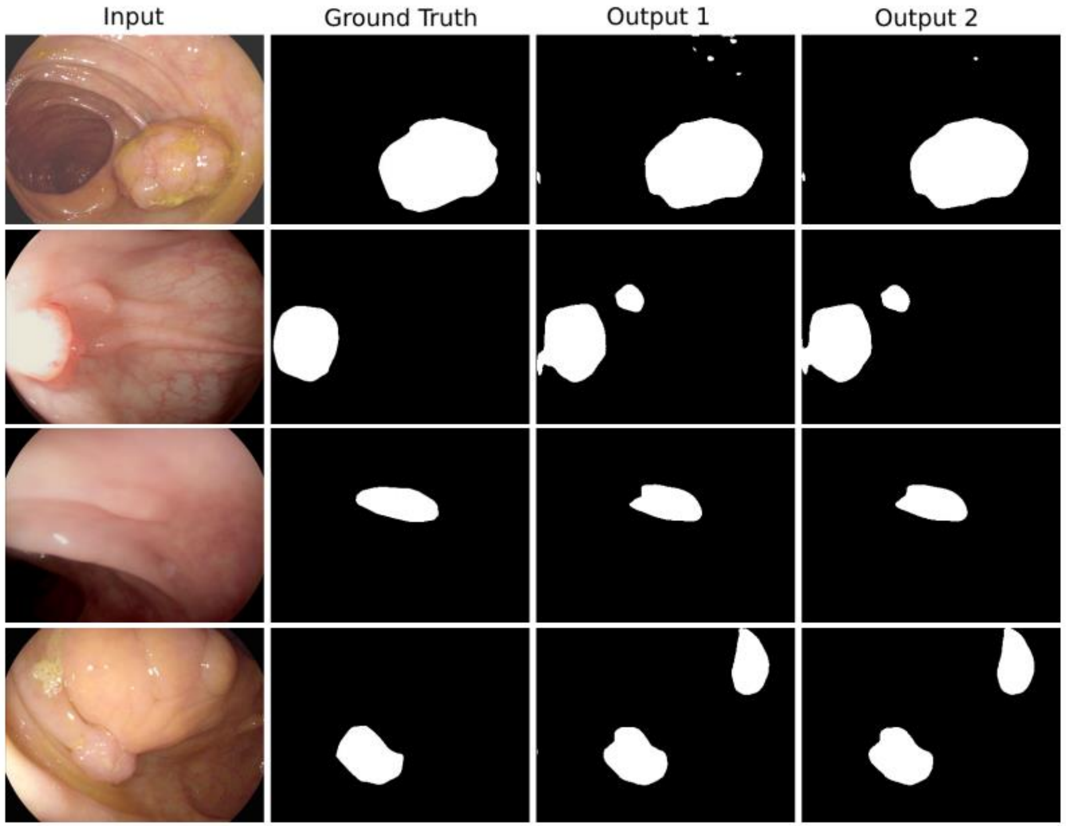
Results

A. Comparison on 2015 MICCAI sub-challenge on automatic polyp detection dataset

EXPERIMENTAL RESULTS USING THE 2015 MICCAI SUB-CHALLENGE ON AUTOMATIC POLYP DETECTION DATASET

Method	DSC	mIoU	Recall	Precision
FCN-VGG [28]	0.7023	0.5420	-	-
Mask R-CNN with Resnet101 [29]	0.7042	0.6124	-	-
U-Net	0.2920	0.1759	0.5930	0.2021
DoubleU-Net	**0.7649**	**0.6255**	**0.7156**	**0.8007**

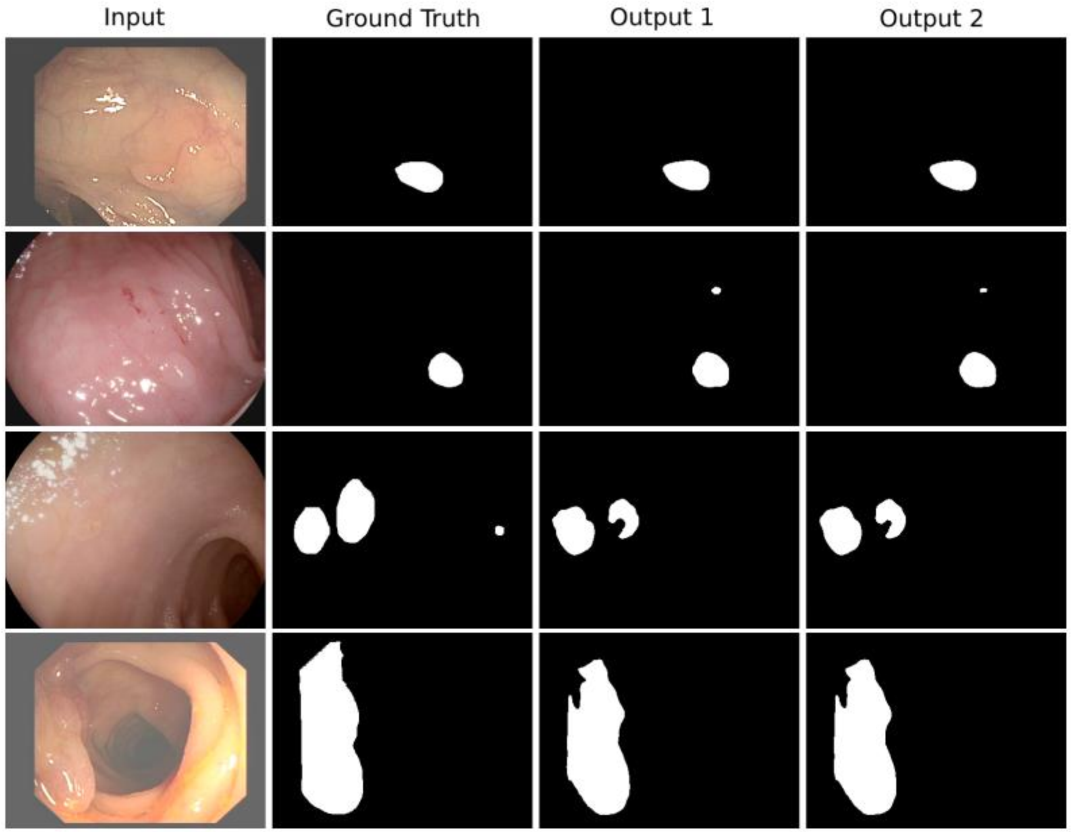




Results
B. Comparison on CVC-ClinicDB

RESULT COMPARISON ON CVC-CLINICDB

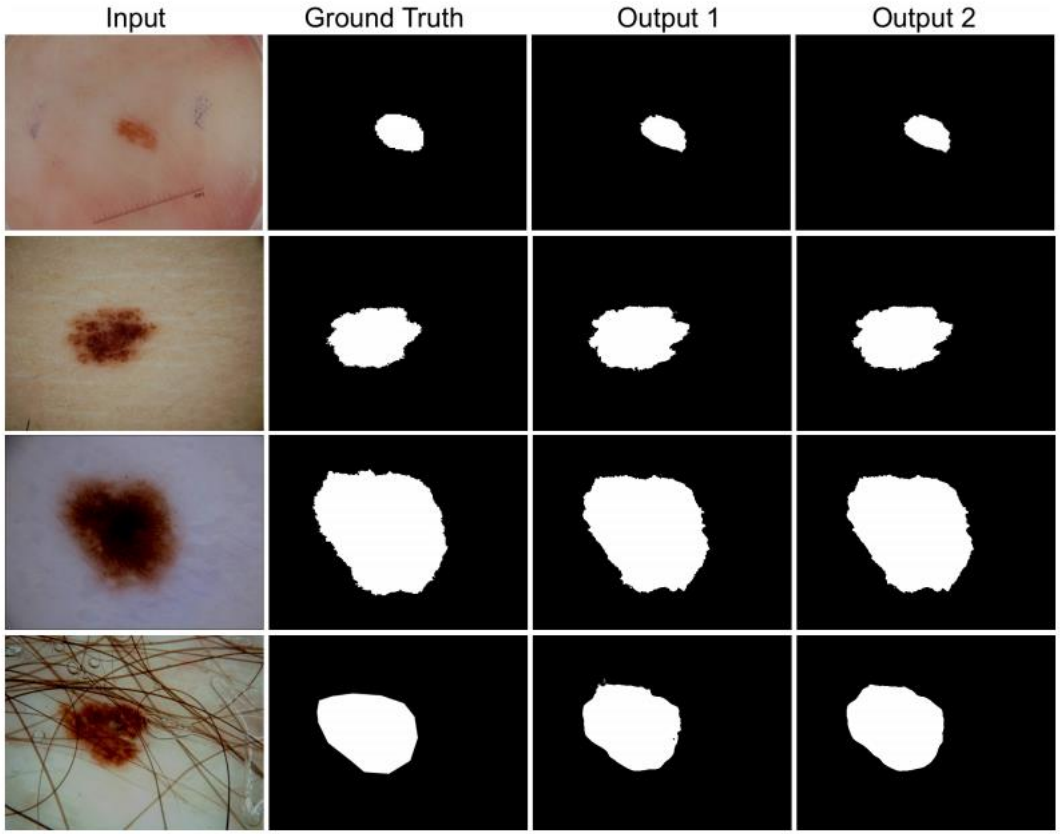
Method	DSC	mIoU	Recall	Precision
Fully Convoutional Network [30]	-	-	0.7732	0.8999
CNN [31]	(0.62-0.87)	-	-	-
SegNet [32]	-	-	**0.8824**	-
Multi-scale patch-based CNN [33]	0.8130	-	0.7860	0.8090
MultiResUNet with data augmentation [17]	-	0.8497	-	-
Conditional generative adversarial network [34]	0.8848	0.8127	-	-
U-Net	0.8781	0.7881	0.7865	0.9329
DoubleU-Net	**0.9239**	**0.8611**	0.8457	**0.9592**



Results
C. Comparison on Lesion Boundary segmentation challenge dataset.

RESULT ON LESION BOUNDARY SEGMENTATION DATASET FROM ISIC-2018

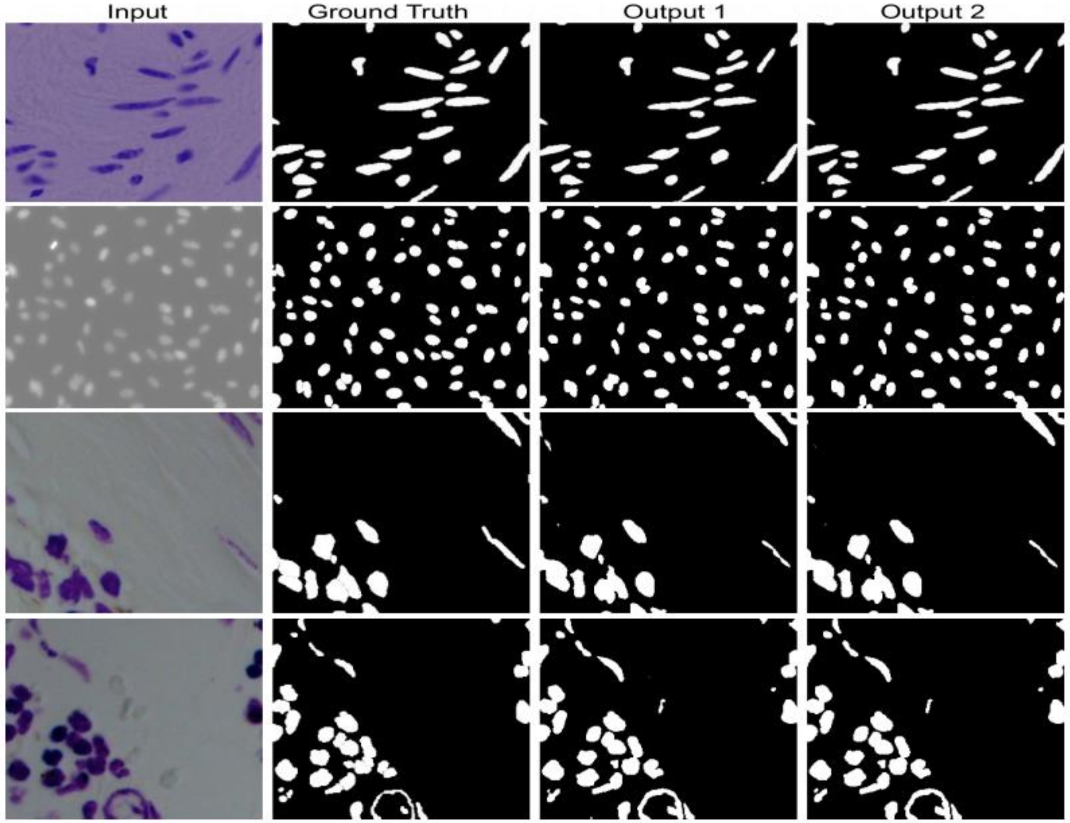
Method	DSC	mIoU	Recall	Precision
U-Net [17]	-	0.7642 ± 0.4518	-	-
Multi-ResUNet [17]	-	0.8029 ± 0.3717	-	-
DoubleU-Net	**0.8962**	**0.8212**	**0.8780**	**0.9459**



Results
D. Comparison on 2018 Data Science Bowl challenge dataset.

RESULT ON NUCLEI SEGMENTATION FROM 2018 DATA SCIENCE BOWL CHALLENGE

Method	Pre-trained network	DSC	mIoU	Recall	Precision
U-Net [20]	Resnet101	0.7573	0.9103	-	-
UNet++ [20]	Resnet101	0.8974	**0.9255**	-	-
DoubleU-Net	VGG-19	**0.9133**	0.8407	**0.6407**	**0.9496**



Discussion

RELATIVE IMPROVEMENT OF DOUBLEU-NET ON U-NET

Modality	U-Net (DSC)	DoubleU-Net (DSC)	Overall Improvement
Colonoscopy (MICCAI 2015)	0.2920	0.7649	0.4729
Colonoscopy (CVC-ClinicDB)	0.8781	0.9239	0.0458
Dermoscopy (ISIC-2018)	–	0.8962	–
Microscopy (2018 Data Science Bowl)	0.7573	0.9133	0.1560

Table VI shows the DSC comparison of U-Net and DoubleU-Net. From the above table, we can see that DoubleU-Net performs reasonably well as compared to U-Net for all the presented datasets.

Conclusions, limitations and future work

The main contributions of this work were:

- A novel architecture, DoubleU-Net, for se-mantic image segmentation were proposed.
- An extensive evaluation of DoubleU-Net across four dataset shows a significant improvement over U-Net. Therefore, DoubleU-Net can be a new baseline for medical image segmentation task.
- The proposed architecture is flexible, and that makes it possible to integrate other CNN blocks into DoubleU-Net.
- A limitation of the DoubleU-Net is that it uses more parameters as compared to U-Net, which leads to an increase in the training time.

Referencias

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Gracias....