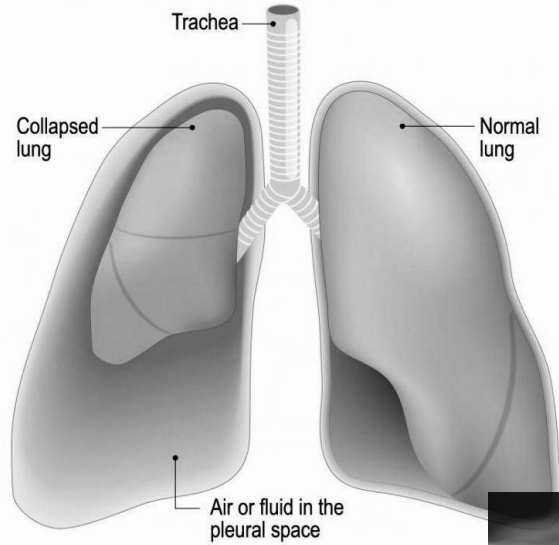


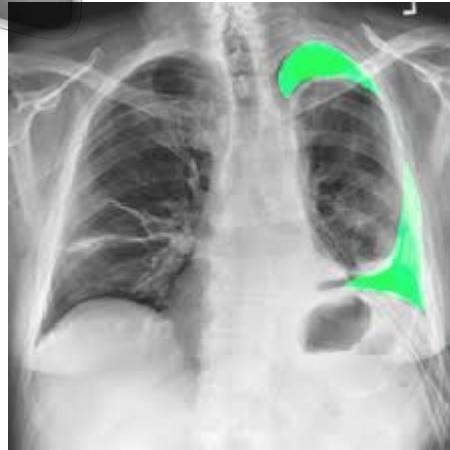
Chest X-Ray Pneumothorax images segmentation

by Aleksandra Shchetinina (a.shchetinina@innopolis.ru)
& Anastasia Pichka (a.pichka@innopolis.ru)
BS17-RO

Intro

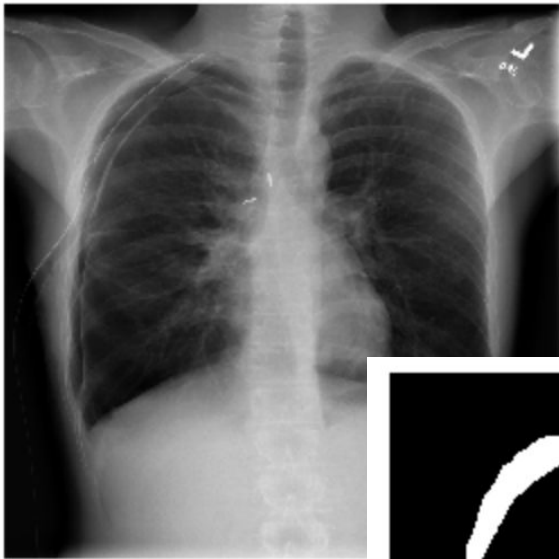


CHEST X-RAY



Pneumothorax

Collapse of the lung, occurs when the chest and lungs are injured, as well as certain lung conditions (eg, tuberculosis, pneumonia)



PNEUMOTHORAX



Dataset

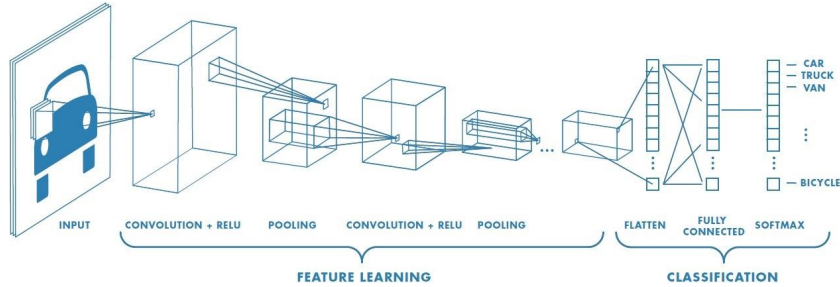
12,047 chest x-ray images
12,047 pneumothorax
masks

Size - 1024x1024, in png
format

Segmentation

Process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects)

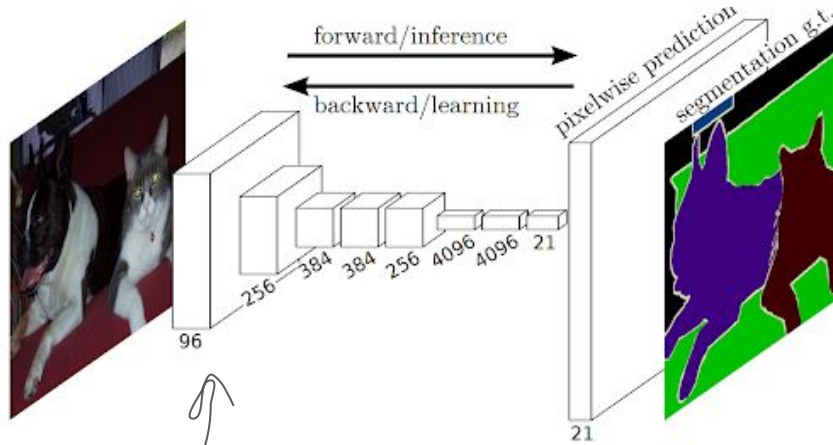




CNN

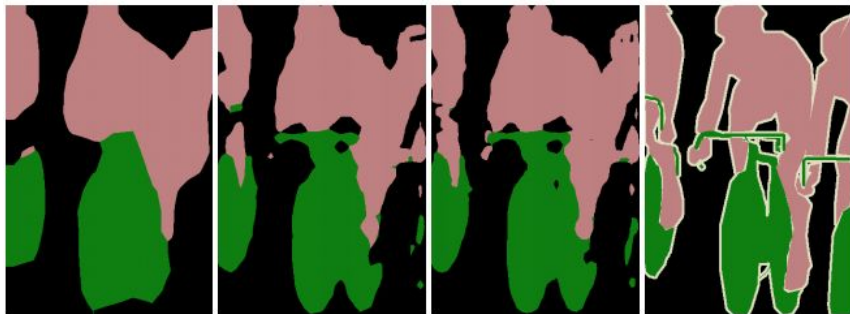
FCN - Fully Convolutional Network

Last fully connected layer of such network was replaced with a fully convolutional layer, produce a dense pixel-wise prediction



FCN

Related Work



Fully Convolutional Networks for Semantic Segmentation

Jonathan Long, Evan Shelhamer, Trevor Darrell

8 Mar 2015

AlexNet, VGG, GoogLeNet can be adopted using transfer learning by fine-tuning and used for segmentation

	FCN-AlexNet	FCN-VGG16	FCN-GoogLeNet ⁴
mean IU	39.8	56.0	42.5
forward time	50 ms	210 ms	59 ms
conv. layers	8	16	22
parameters	57M	134M	6M
rf size	355	404	907
max stride	32	32	32

Idea Explanation

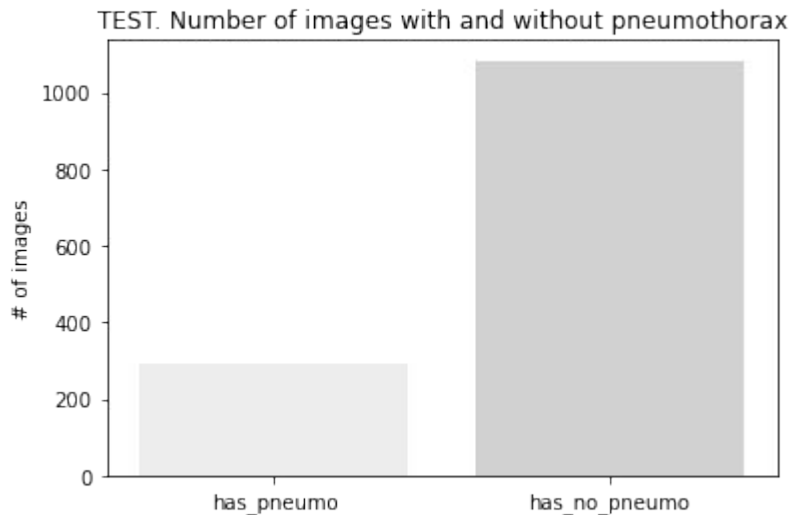
	new_filename	ImageId	has_pneumo
0	0_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.5597.151787518...	0
1	1_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.12515.15178752...	0
2	2_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.4904.151787518...	1
3	3_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.32579.15178751...	1
4	4_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.1314.151787516...	1
5	5_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.11364.15178752...	0
6	6_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.4541.151787518...	0
7	7_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.4440.151787518...	1
8	8_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.4982.151787518...	1
9	9_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.31759.15178751...	0
10	10_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.12743.15178752...	1
11	11_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.11633.15178752...	1
12	12_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.11512.15178752...	0
13	13_train_1_.png	1.2.276.0.7230010.3.1.4.8323329.2663.151787517...	1
14	14_train_0_.png	1.2.276.0.7230010.3.1.4.8323329.10206.15178752...	0

Data Preparation

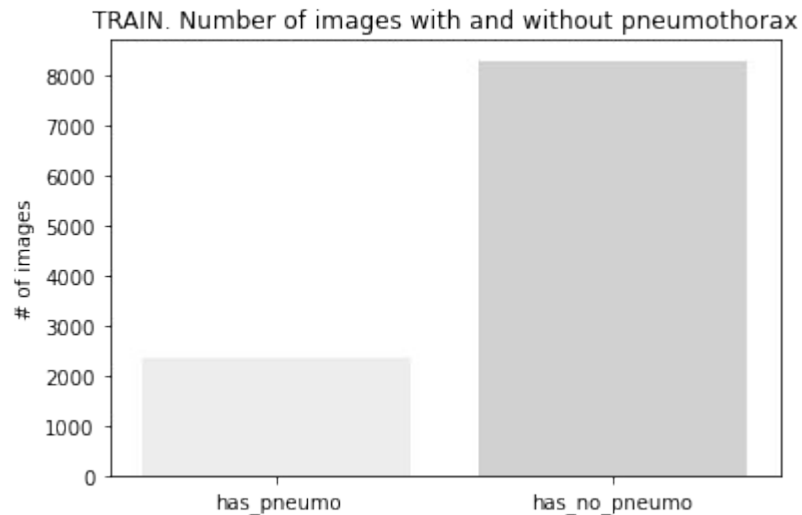
The data is taken from the dataset and prepared (normalized, resized, divided into test and train, etc). Masks (segmented image) is also prepared

Imbalanced data

TEST



TRAIN



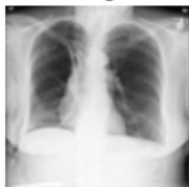
Image



Mask
Label: 1



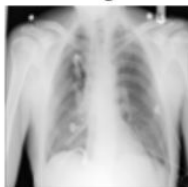
Image



Mask
Label: 1



Image



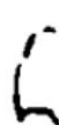
Mask
Label: 1



Image



Mask
Label: 1



Image



Mask
Label: 1



Image



Mask
Label: 1



Image



Mask
Label: 1



Image



Mask
Label: 1



Image



Mask
Label: 1



Image



Mask
Label: 1



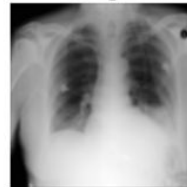
Image



Mask
Label: 1



Image

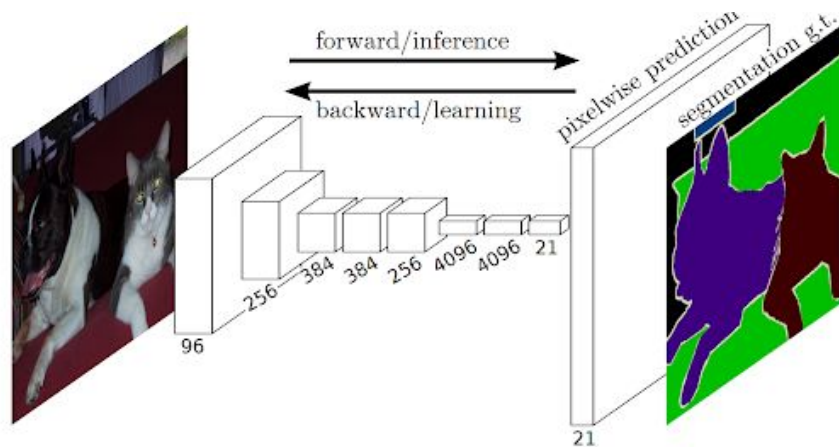


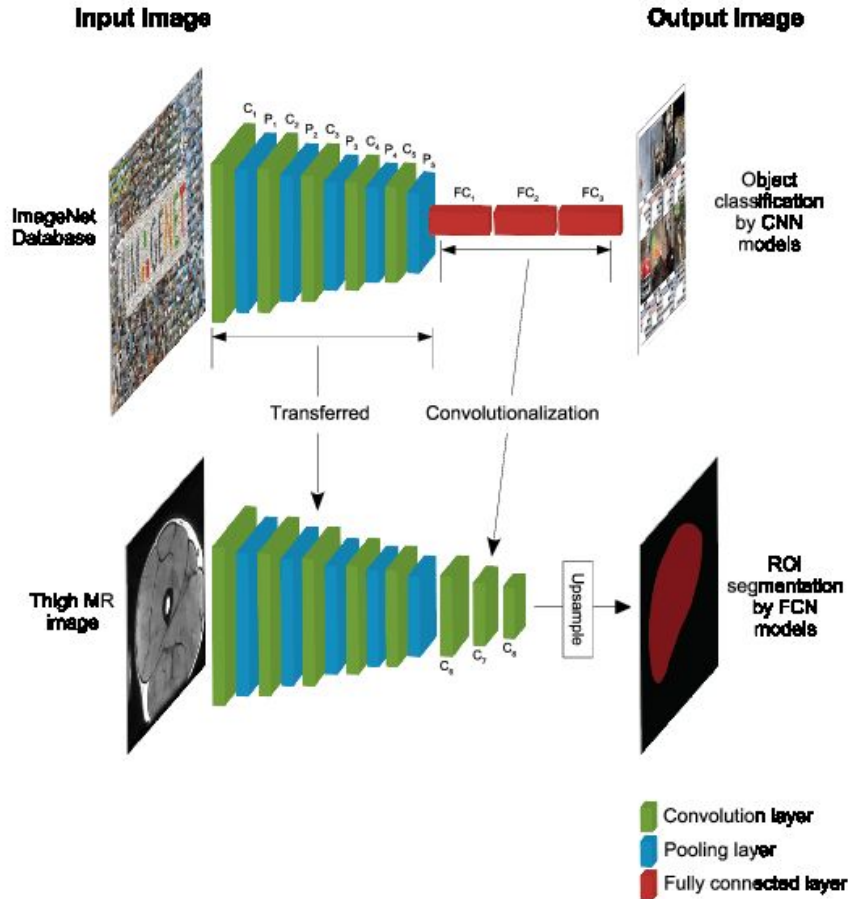
Mask
Label: 1



Model

The basic idea behind a fully convolutional network is that it is “fully convolutional”, so all of its layers are convolutional layers. FCNs don’t have any of the fully-connected layers at the end, which are typically used for classification. Instead, FCNs use convolutional layers to classify each pixel in the image.





Transfer Learning

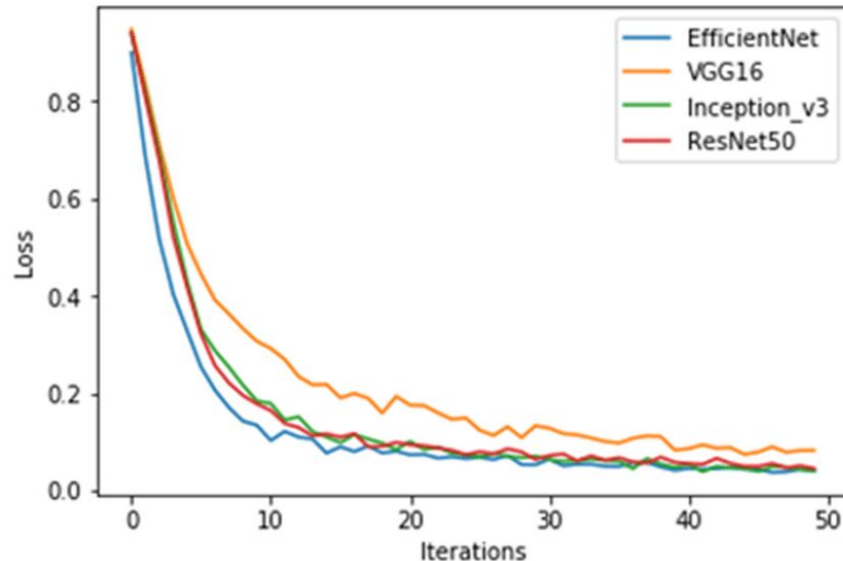
Research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem

Architecture

Architecture:

- Pre-trained classifier without fully-connected layers (transferred, frozen)
- Convolution layers
- Upsampling(Deconvolution)
- Softmax layer

→ VGG
→ RESNET
→ INCEPTIONV3



VGG

```
-----  
Layer (type)                Output Shape                Param #  
=====
```

vgg19 (Functional)	(None, 4, 4, 512)	20024384

conv2d_transpose (Conv2DTran	(None, 16, 16, 2)	262146

dropout (Dropout)	(None, 16, 16, 2)	0

conv2d_transpose_1 (Conv2DTr	(None, 64, 64, 2)	4098

dropout_1 (Dropout)	(None, 64, 64, 2)	0

conv2d_transpose_2 (Conv2DTr	(None, 128, 128, 2)	16386

activation (Activation)	(None, 128, 128, 2)	0
=====		
Total params: 20,307,014		
Trainable params: 282,630		
Non-trainable params: 20,024,384		

RESNET

Layer (type)	Output Shape	Param #
resnet50 (Model)	(None, 4, 4, 2048)	23587712
conv2d_transpose_14 (Conv2DT	(None, 8, 8, 2)	65538
dropout_10 (Dropout)	(None, 8, 8, 2)	0
conv2d_transpose_15 (Conv2DT	(None, 16, 16, 2)	1026
dropout_11 (Dropout)	(None, 16, 16, 2)	0
conv2d_transpose_16 (Conv2DT	(None, 32, 32, 2)	4098
dropout_12 (Dropout)	(None, 32, 32, 2)	0
conv2d_transpose_17 (Conv2DT	(None, 64, 64, 2)	4098
dropout_13 (Dropout)	(None, 64, 64, 2)	0
conv2d_transpose_18 (Conv2DT	(None, 128, 128, 2)	16386
activation_4 (Activation)	(None, 128, 128, 2)	0
Total params: 23,678,858		
Trainable params: 91,146		
Non-trainable params: 23,587,712		

INCEPTIONV3

Layer (type)	Output Shape	Param #
inception_v3 (Model)	(None, 2, 2, 2048)	21802784
conv2d_transpose_27 (Conv2DT	(None, 8, 8, 2)	1048578
dropout_15 (Dropout)	(None, 8, 8, 2)	0
conv2d_transpose_28 (Conv2DT	(None, 32, 32, 2)	4098
dropout_16 (Dropout)	(None, 32, 32, 2)	0
conv2d_transpose_29 (Conv2DT	(None, 64, 64, 2)	4098
dropout_17 (Dropout)	(None, 64, 64, 2)	0
conv2d_transpose_30 (Conv2DT	(None, 128, 128, 2)	16386
activation_289 (Activation)	(None, 128, 128, 2)	0
Total params: 22,875,944		
Trainable params: 1,073,160		
Non-trainable params: 21,802,784		

Accuracy


Pixel accuracy is conceptually the easiest metric. It is the percent of pixels in image that are classified correctly. The pixel accuracy is commonly reported for each class separately as well as globally across all classes. Also, this metric can be calculated through binary mask (positives and negatives):

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Mean Intersection over Union

Mean IoU is a common evaluation metric for semantic segmentation. Firstly, it computes the IOU for each semantic class and then computes the average over classes. Formula for IOU is the following:

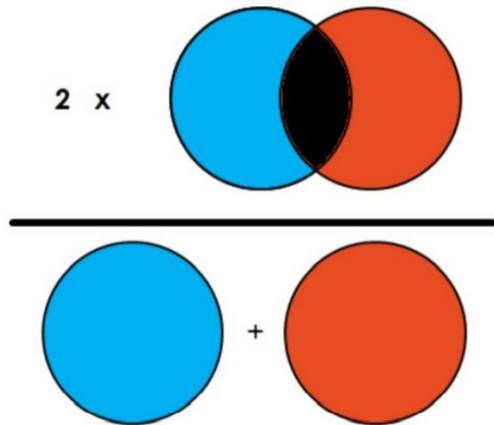
$$\text{IOU} = \frac{\text{truepositive}}{(\text{truepositive} + \text{falsepositive} + \text{falsenegative})}$$

$$\text{IoU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$


Dice coefficient

Dice Coefficient is the area of overlap multiplied by 2 and divided by the total number of pixels in both images. It ranges from 0 to 1, 0 means the smallest similarities between predicted and true, and 1 means the largest.

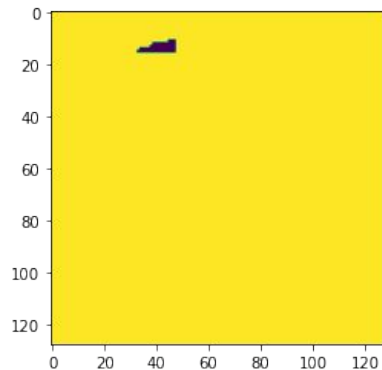
$$\frac{2 * \text{area of overlap}}{\text{total number of pixels}}$$



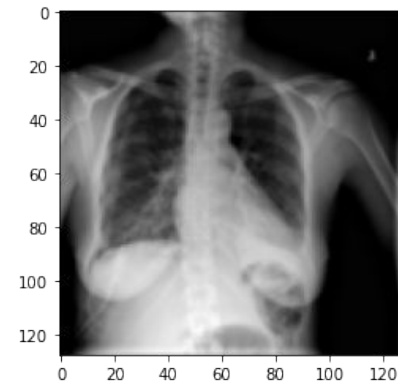
Results

Results, we've got

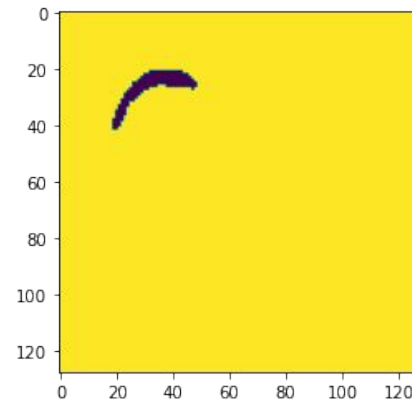
after some training



X_TEST

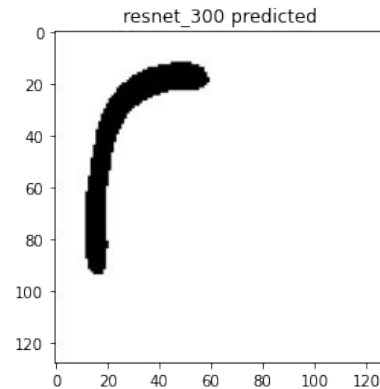
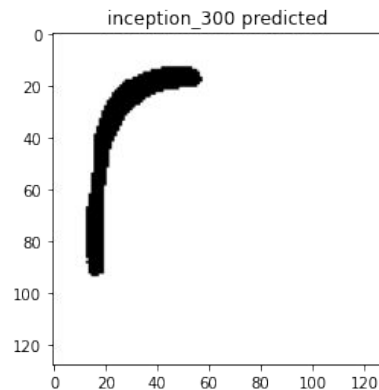
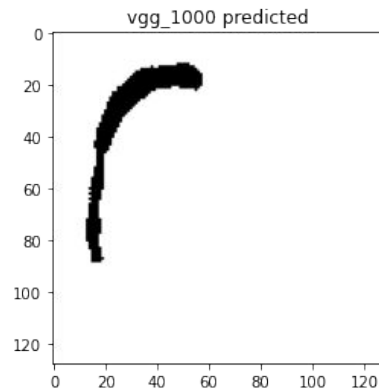
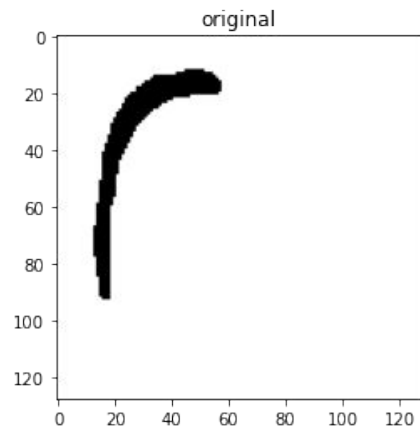
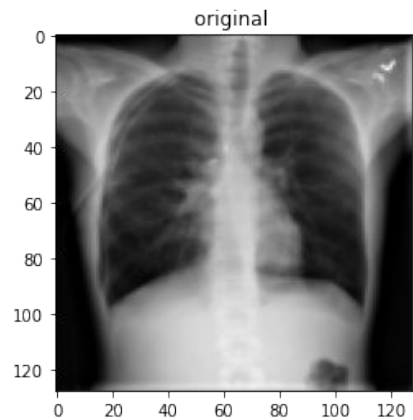


Y_TEST



Example#1

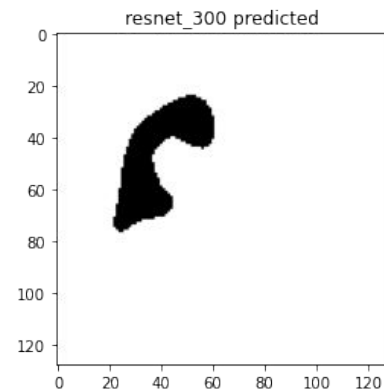
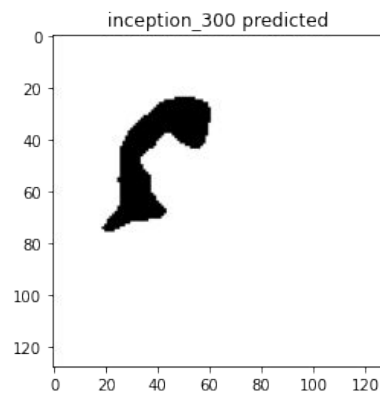
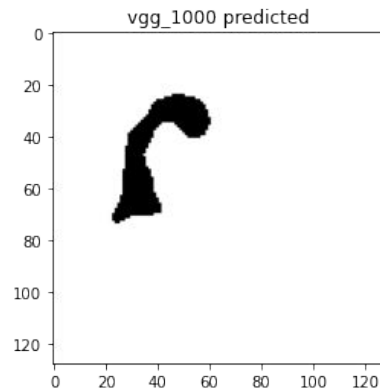
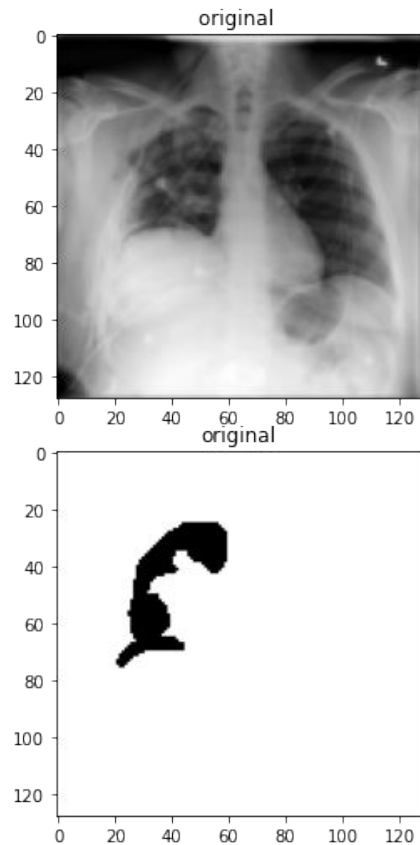
FROM TRAIN



Results

Example#2

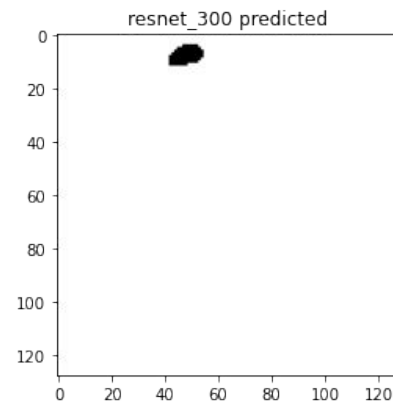
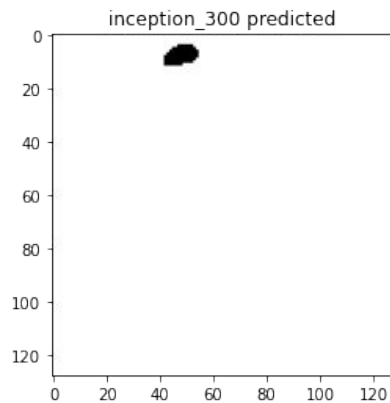
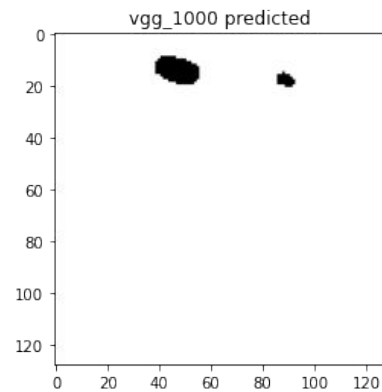
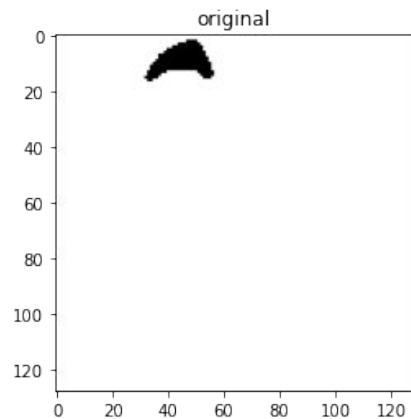
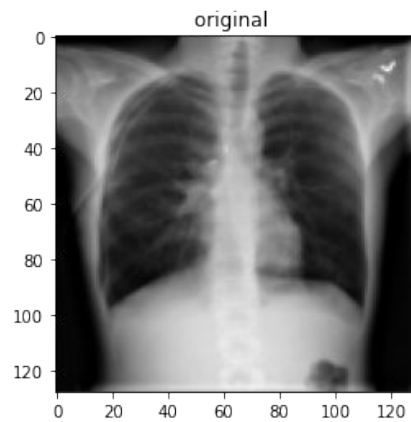
FROM TRAIN



Results

Example#1

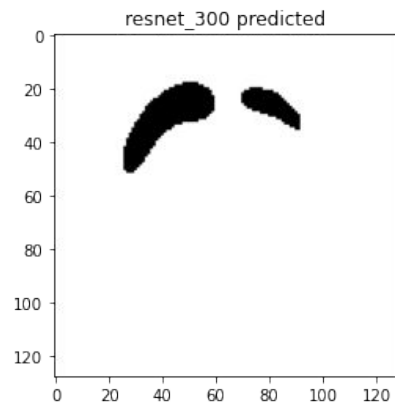
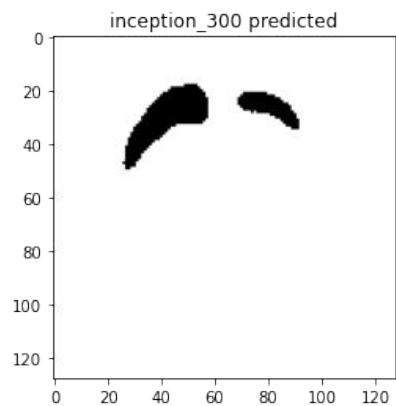
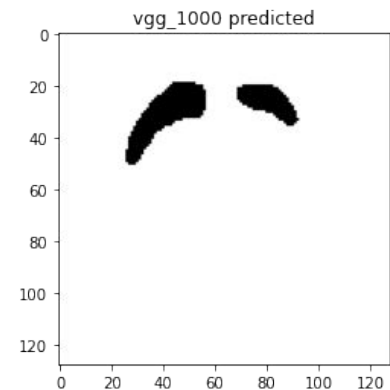
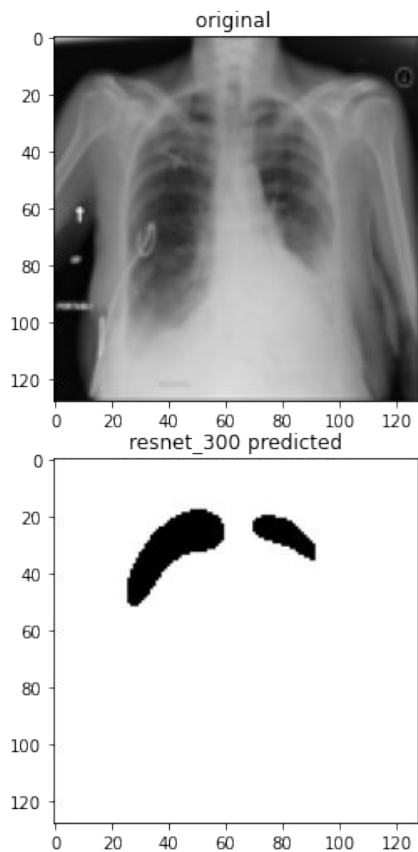
FROM TEST



Results

Example#2

FROM TEST



Results

Accuracy

During training and testing we understood that “accuracy” and “dice” are always high

Epoch 50/100



MEAN IOU

483/483 [=====] - 13s

28ms/step - loss: 0.0444 - accuracy: 0.9840 - mean_io_u: 0.2523 -

dice: -0.9764 - val_loss: 0.0160 - val_accuracy: 0.9954 -

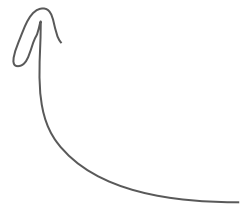
val_mean_io_u: 0.2509 - val_dice: -0.9881

Results

50 100 300

	train	val	test
VGG19_300	0.3012	0.3054	0.3190
ResNet50_300	0.4102	0.4109	0.4302
InsNet_300	0.4409	0.4501	0.4514

MEAN IOU



Conclusions

- Transfer learning and FCN can be used for segmentation
- We can continue training to get even better results
- Also, we can use different configurations of FCN, different loss, optimizers, etc

Thank you