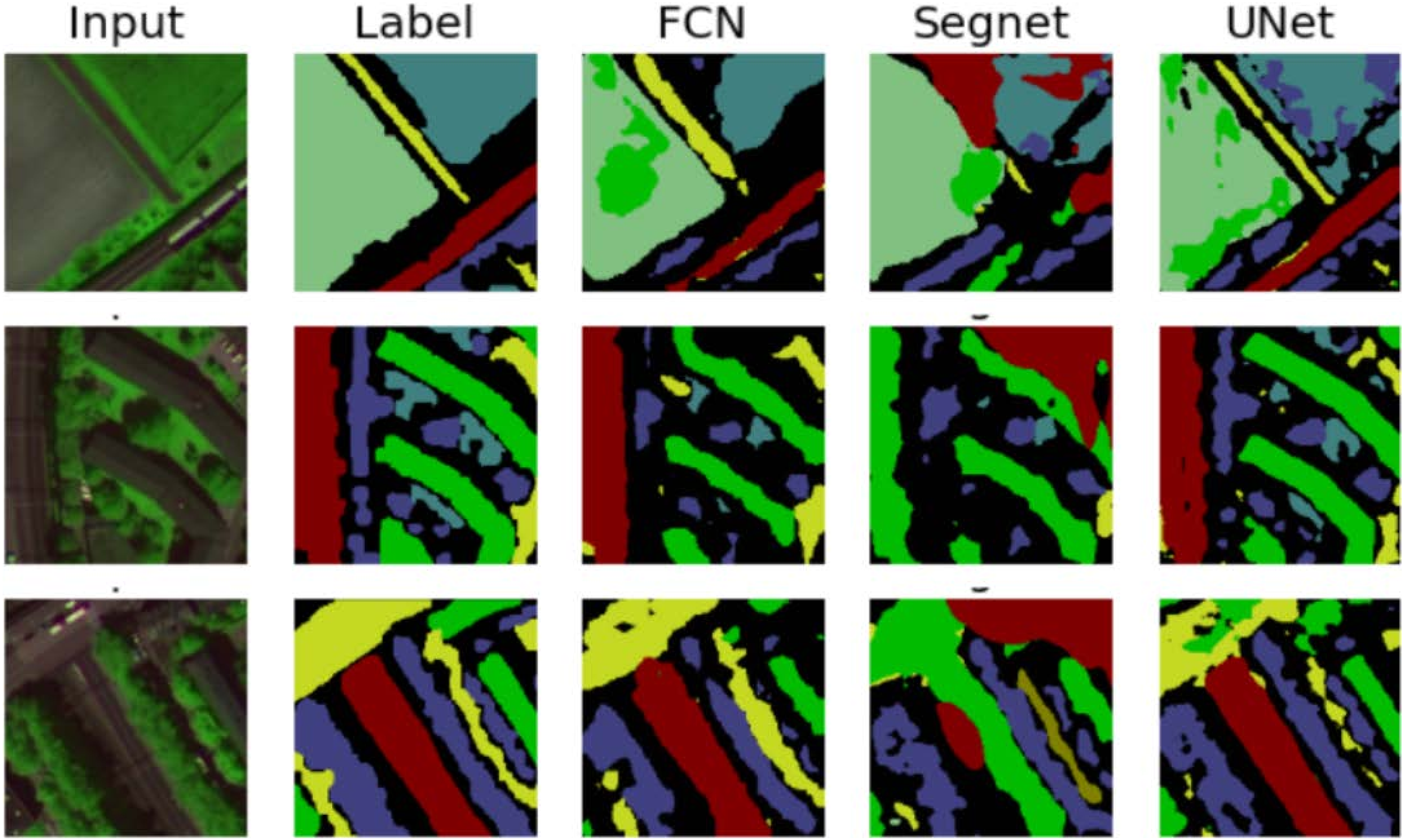
CNN for CV

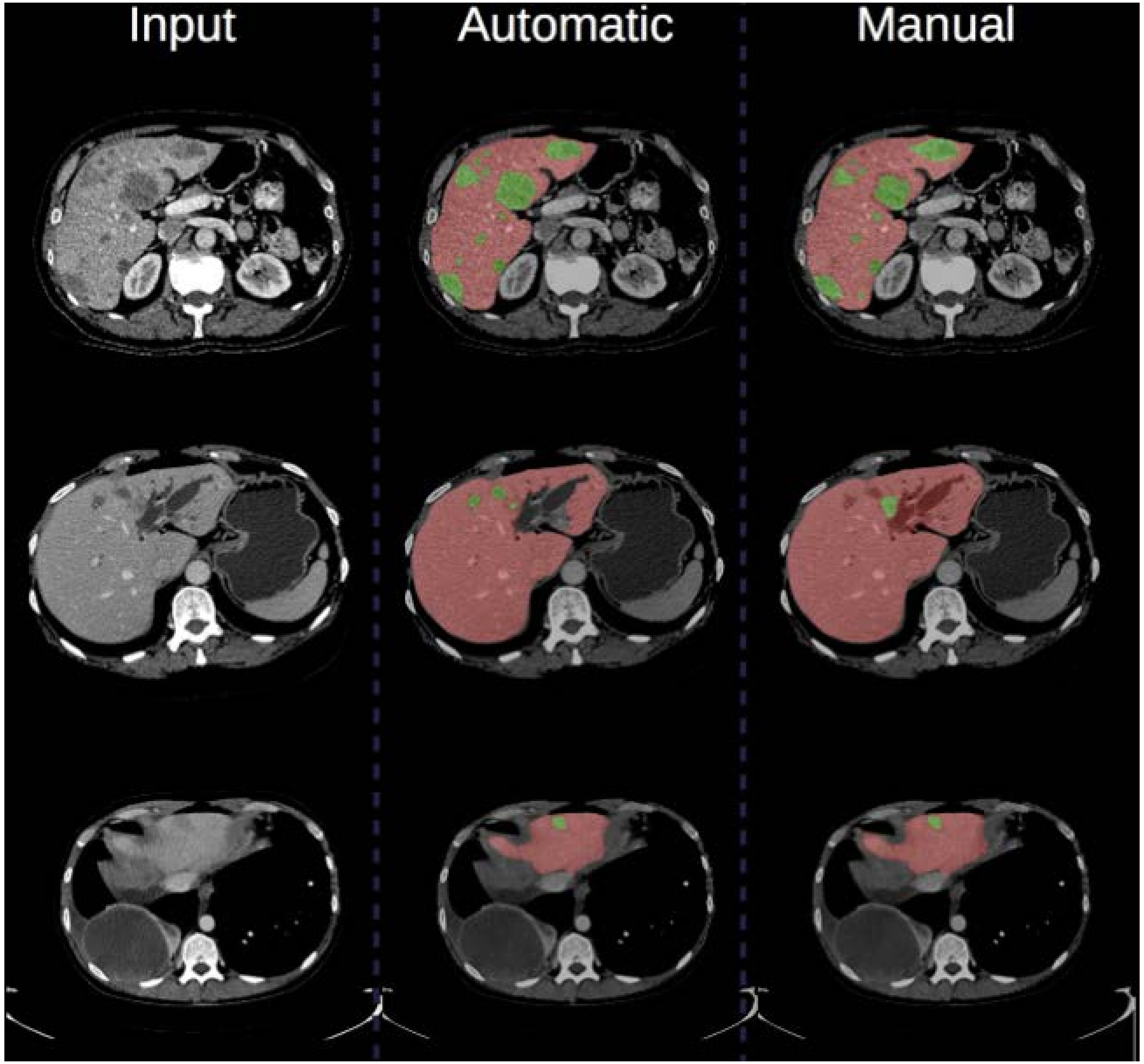
AI for CV Group
2020

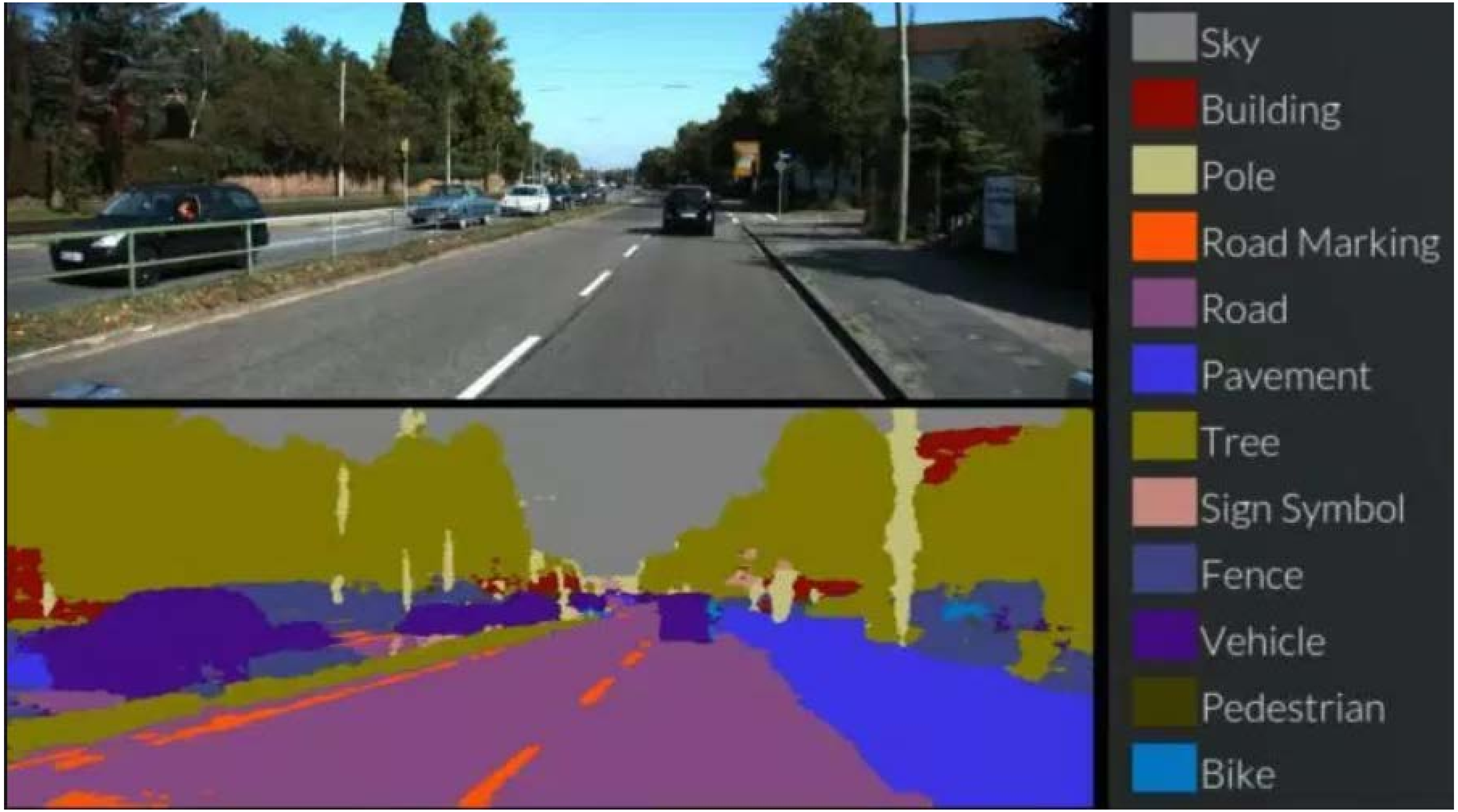
Week 12.
Image Transfer

Contents:

I. Image Segmentation


Input
Label
FCN
Segnet
UNet

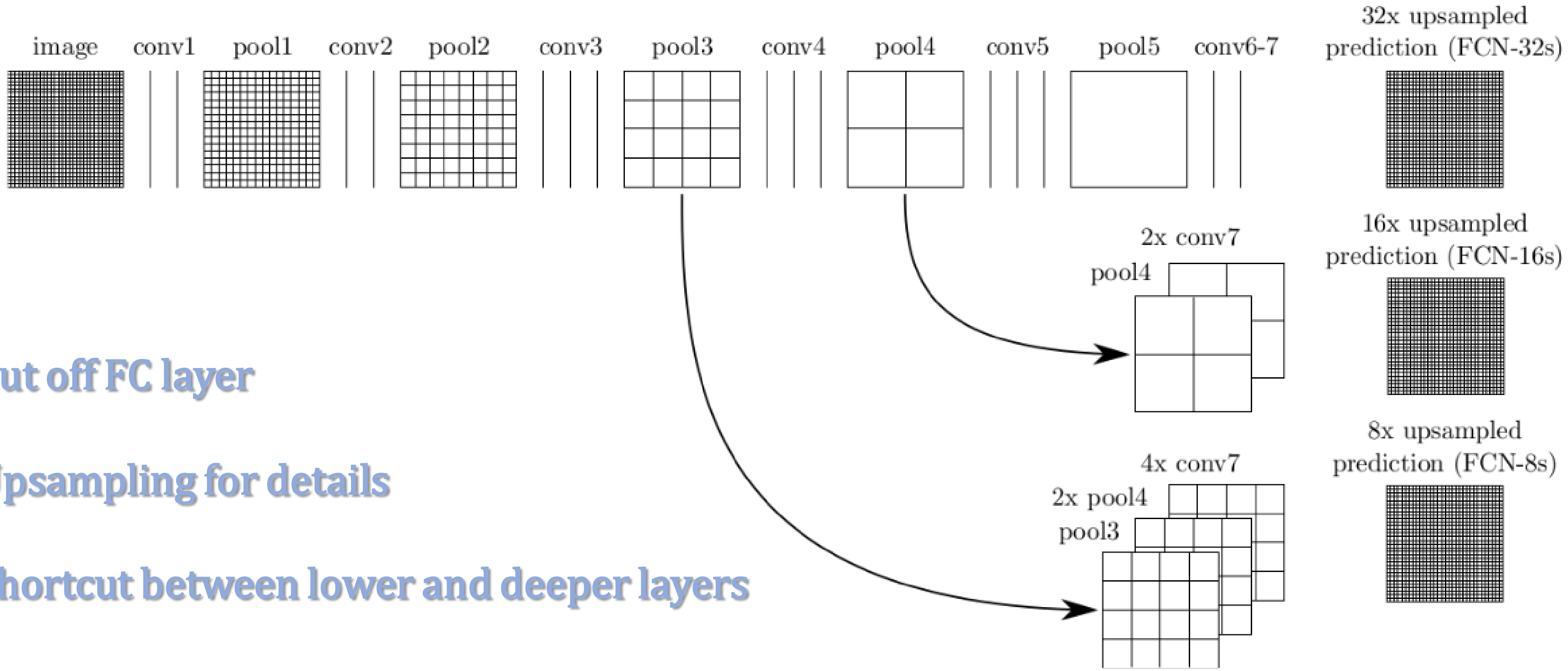

Input
Automatic
Manual


Sky
Building
Pole
Road Marking
Road
Pavement
Tree
Sign Symbol
Fence
Vehicle
Pedestrian
Bike

I. Image Segmentation

A. FCN [2015, Jonathan]:

- **3 Trends:**

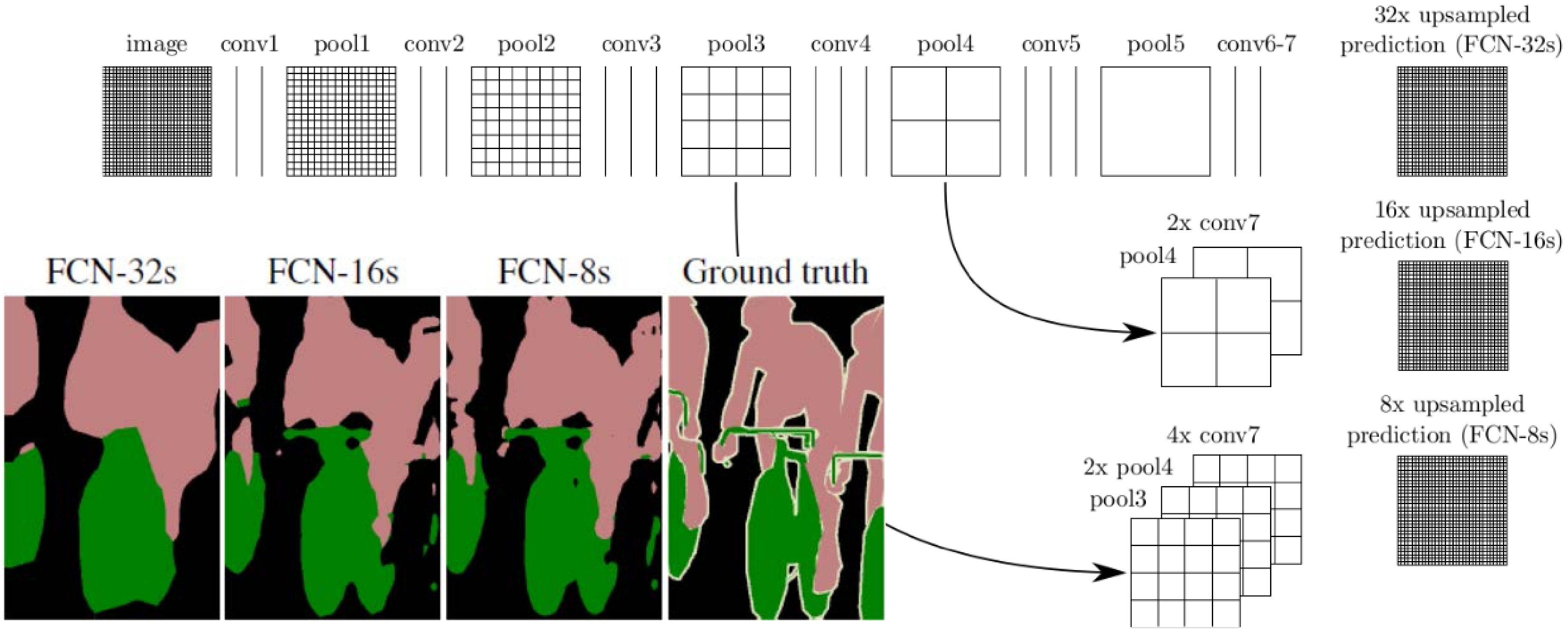


- ➢ **Cut off FC layer**
- ➢ **Upsampling for details**
- ➢ **Shortcut between lower and deeper layers**

I. Image Segmentation

A. FCN [2015, Jonathan]:

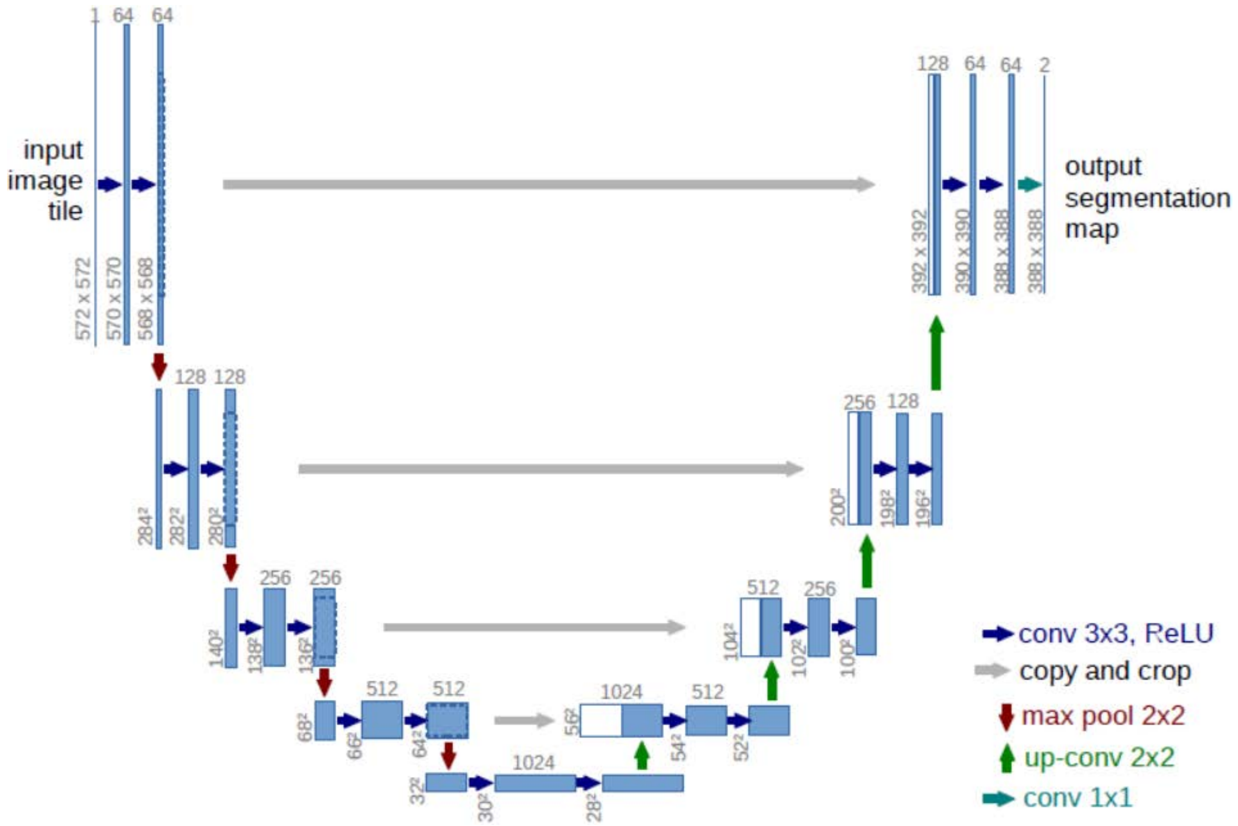
- **Effects:**



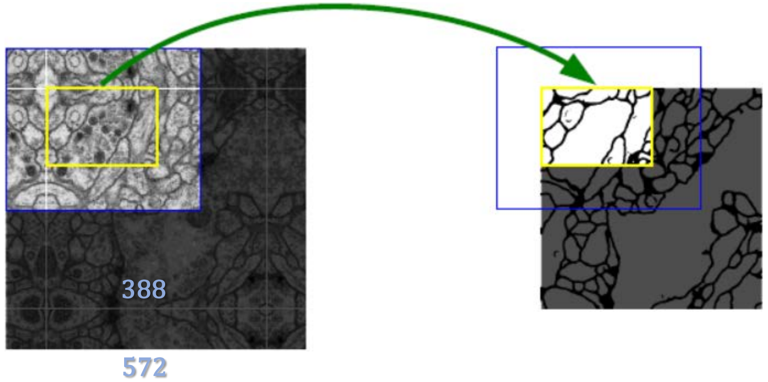
I. Image Segmentation

B. U-Net / E-Net:

B1. U-Net [2015, Olaf]



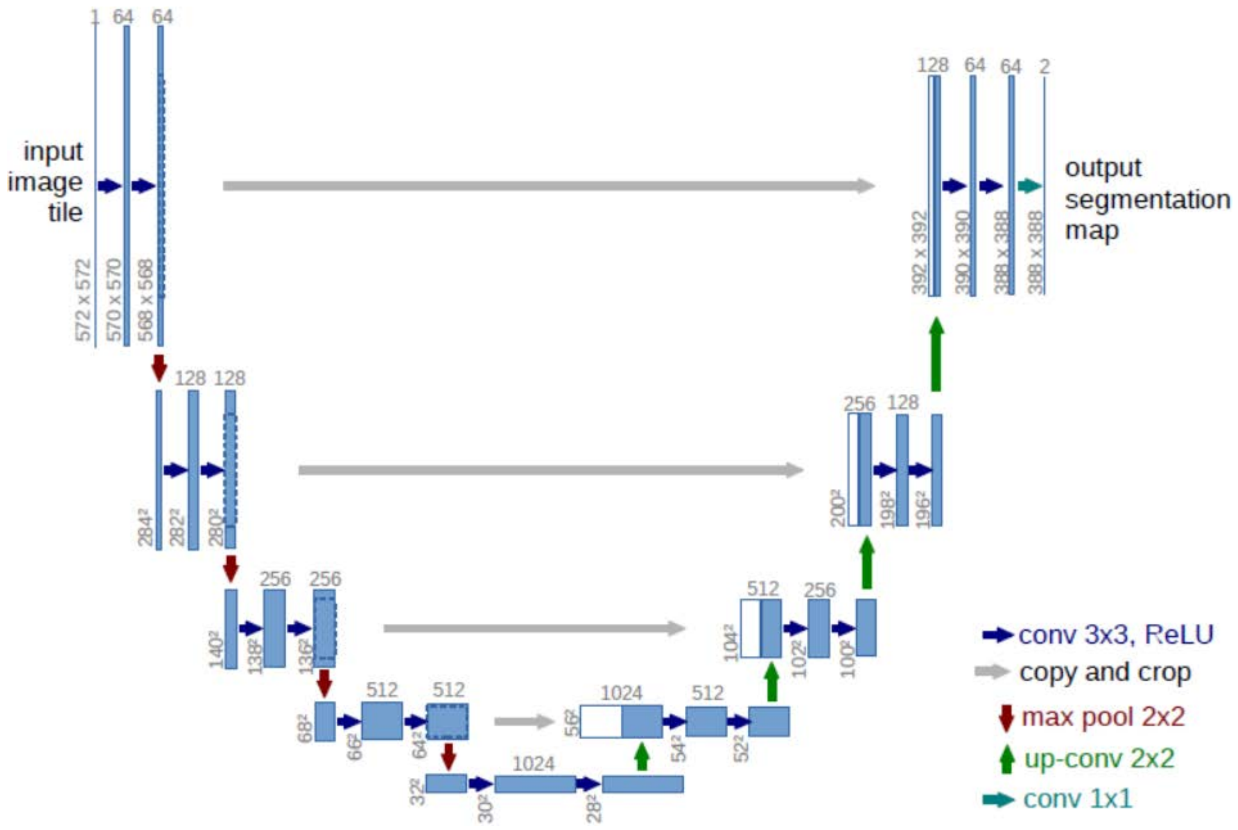
I. Image Segmentation



B. U-Net / E-Net:

B1. U-Net [2015, Olaf]

- **Tile Strategy:**
  - Use padding in mirroring way
  - To due with boarders
  - Just use valid parts
- **U-like Structure**
  - Combine lower & higher info
  - Remove FC layers

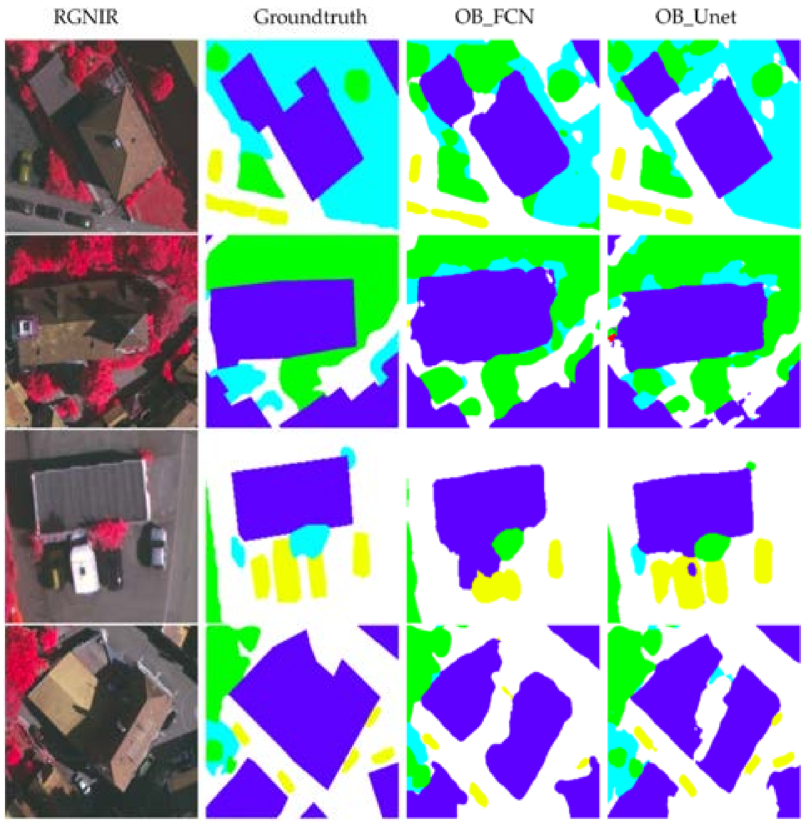


I. Image Segmentation

B. U-Net / E-Net:

B1. U-Net [2015, Olaf]

- **Effects:**

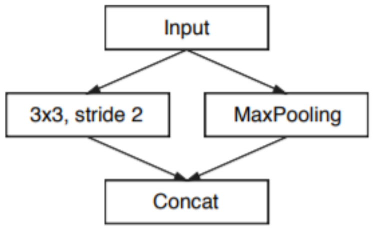


I. Image Segmentation

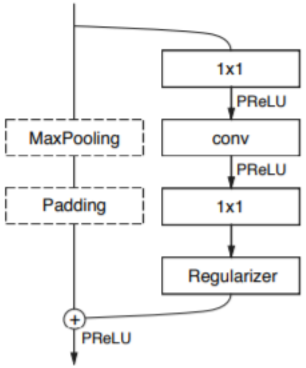
B. U-Net / E-Net:

B2. E-Net [2016, Adam]

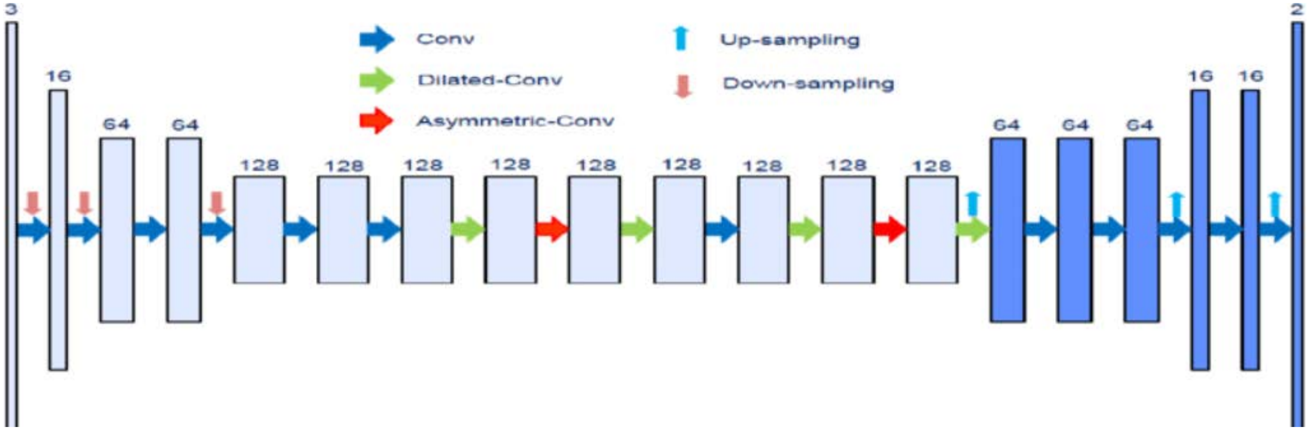
- **Structure:**



(a)



Name	Type	Output size
initial		$16 \times 256 \times 256$
bottleneck1.0	downsampling	$64 \times 128 \times 128$
4× bottleneck1.x		$64 \times 128 \times 128$
bottleneck2.0	downsampling	$128 \times 64 \times 64$
bottleneck2.1		$128 \times 64 \times 64$
bottleneck2.2	dilated 2	$128 \times 64 \times 64$
bottleneck2.3	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.4	dilated 4	$128 \times 64 \times 64$
bottleneck2.5		$128 \times 64 \times 64$
bottleneck2.6	dilated 8	$128 \times 64 \times 64$
bottleneck2.7	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.8	dilated 16	$128 \times 64 \times 64$
Repeat section 2, without bottleneck2.0		
bottleneck4.0	upsampling	$64 \times 128 \times 128$
bottleneck4.1		$64 \times 128 \times 128$
bottleneck4.2		$64 \times 128 \times 128$
bottleneck5.0	upsampling	$16 \times 256 \times 256$
bottleneck5.1		$16 \times 256 \times 256$
fullconv		$C \times 512 \times 512$

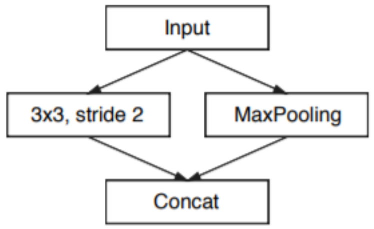


I. Image Segmentation

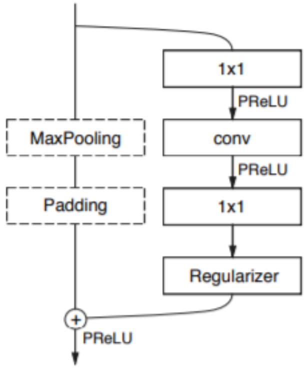
B. U-Net / E-Net:

B2. E-Net [2016, Adam]

- **Features:**
  - ➢ Real Time: Altered bottleneck / Asymmetric conv
  - ➢ Unbalanced Encoder & Decoder
  - ➢ Dilated conv



(a)



Name	Type	Output size
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bottleneck1.0	downsampling	64 × 128 × 128
4× bottleneck1.x		64 × 128 × 128
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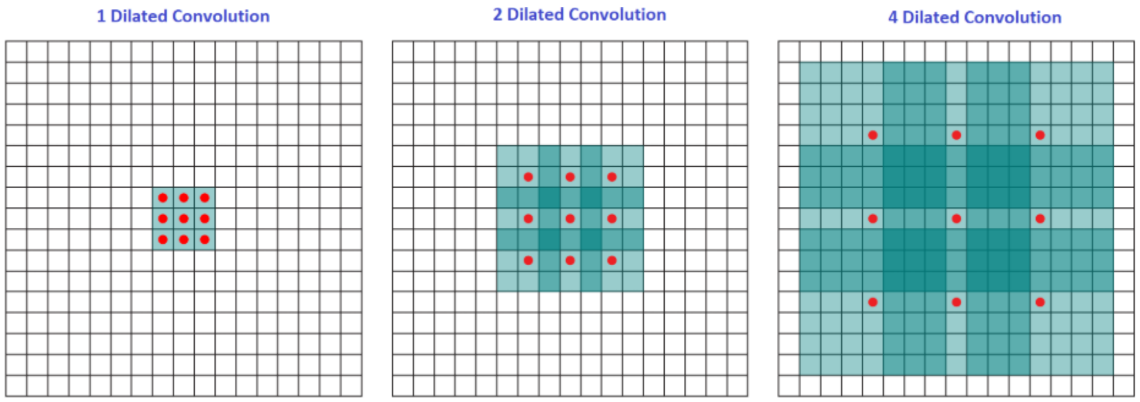
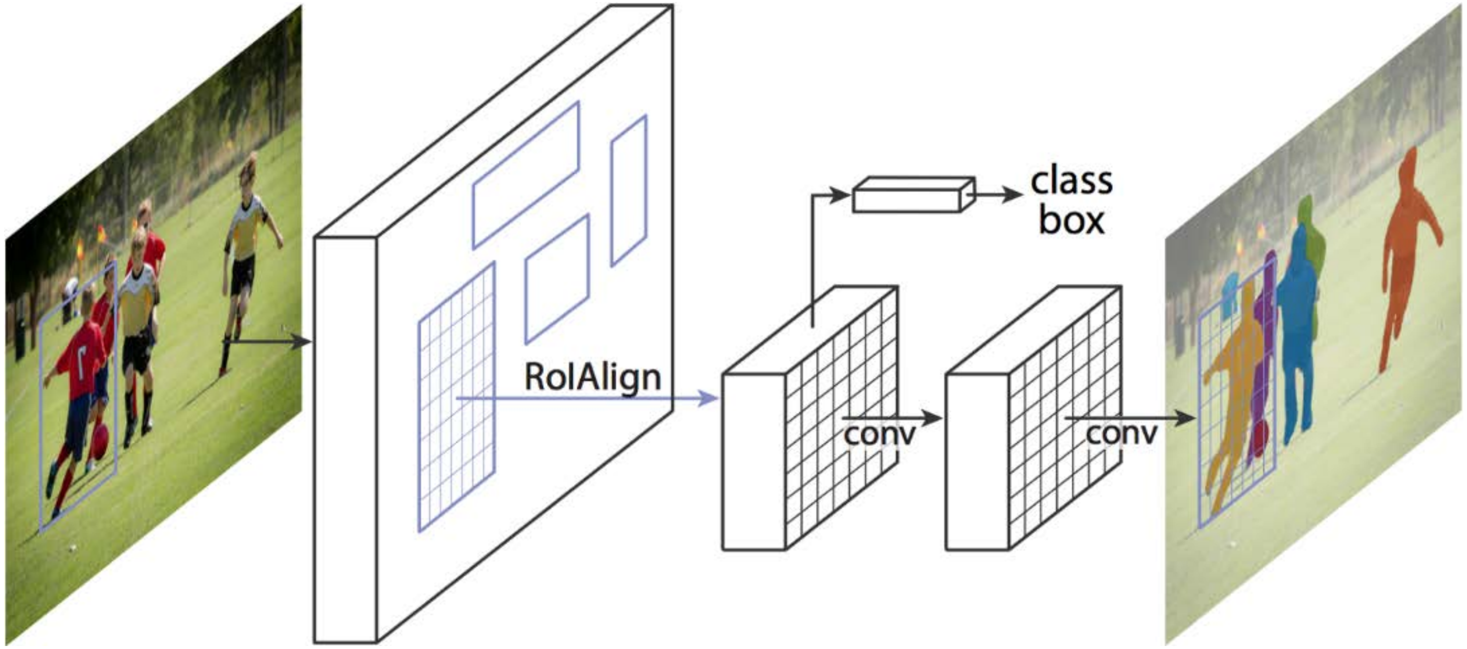
bottleneck4.0	upsampling	64 × 128 × 128
bottleneck4.1		64 × 128 × 128
bottleneck4.2		64 × 128 × 128
bottleneck5.0	upsampling	16 × 256 × 256
bottleneck5.1		16 × 256 × 256
fullconv		$C \times 512 \times 512$



I. Image Segmentation

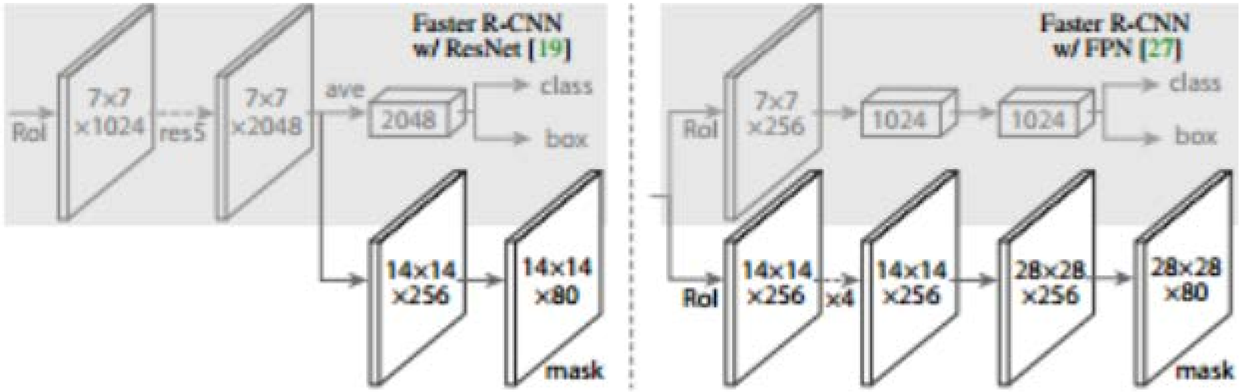
C. Mask-RCNN [2017, He]:



I. Image Segmentation

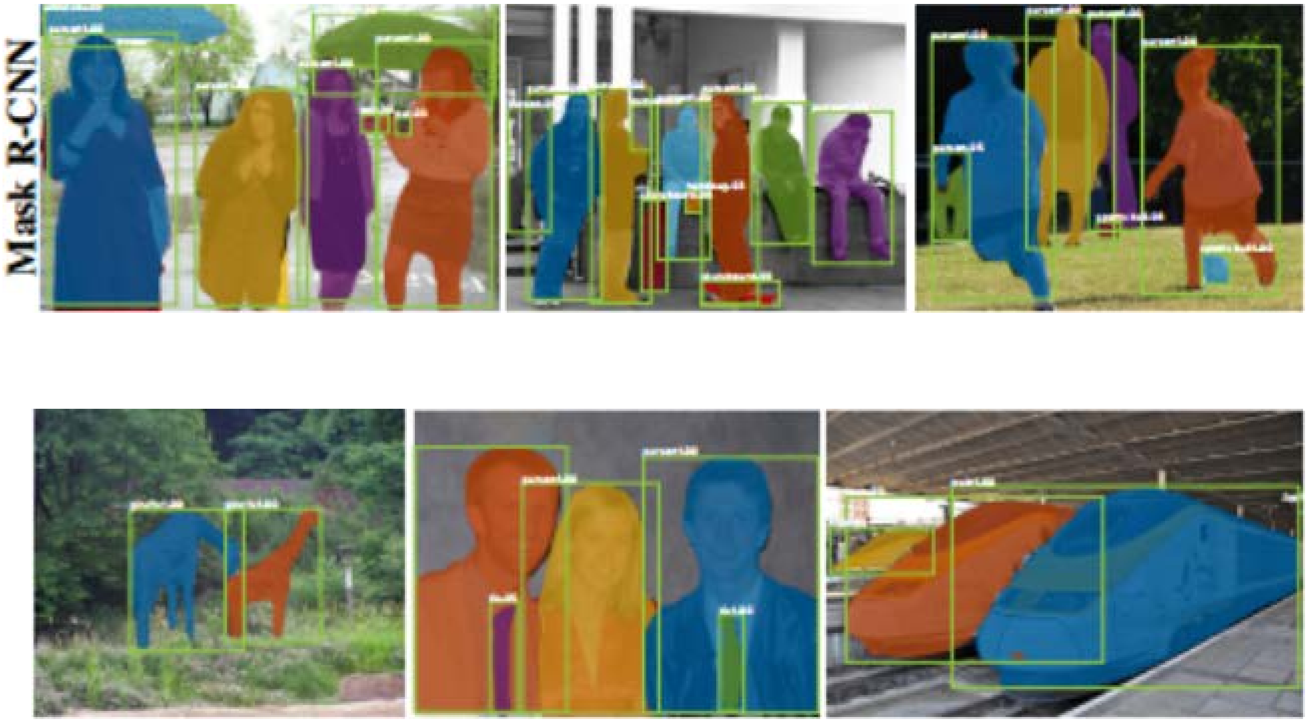
C. Mask-RCNN [2017, He]:

- **Features:**
  - ➢ Use FPN as backbone
  - ➢ Add FCN for each proposal as mask branch
  - ➢ ROI Align
  - ➢ Classify, mask and detect separately / FCN: classify with mask together
  - ➢ 5 fps



I. Image Segmentation

C. Mask-RCNN [2017, He]:



I. Image Segmentation

D. Developments:

- FCN
- Upsampling method: Deconv —> Interpolation
- FCN with CRF / other traditional methods
- Dilated conv
- Backbone dev: VGG, Resnet, …
- Pyramid
- Multi-stage: ICNet [Cascade]
- Semi/non-supervised learning [A paper]

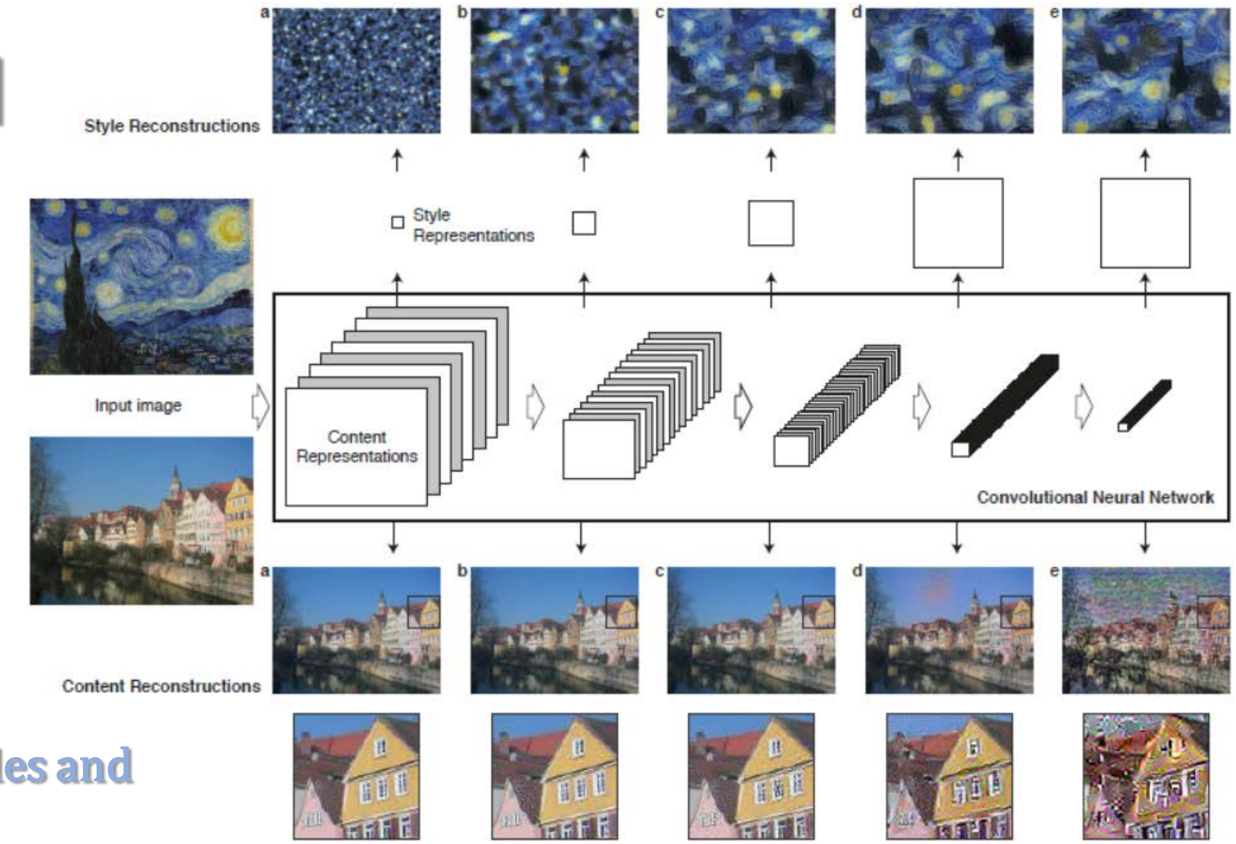
II. Image Style Transfer

II. Image Style Transfer

E. Image Style Transfer

E1. 1st Trial [2015, Gatys]

- **Arguments:**
  - ➢ Images can be represented by contents and styles
  - ➢ The higher a layer is, the more semantic info we'll get; The lower a layer is, the more loca info we'll get.
  - ➢ We can transfer an image's style by minimizing the loss of their styles and contents.

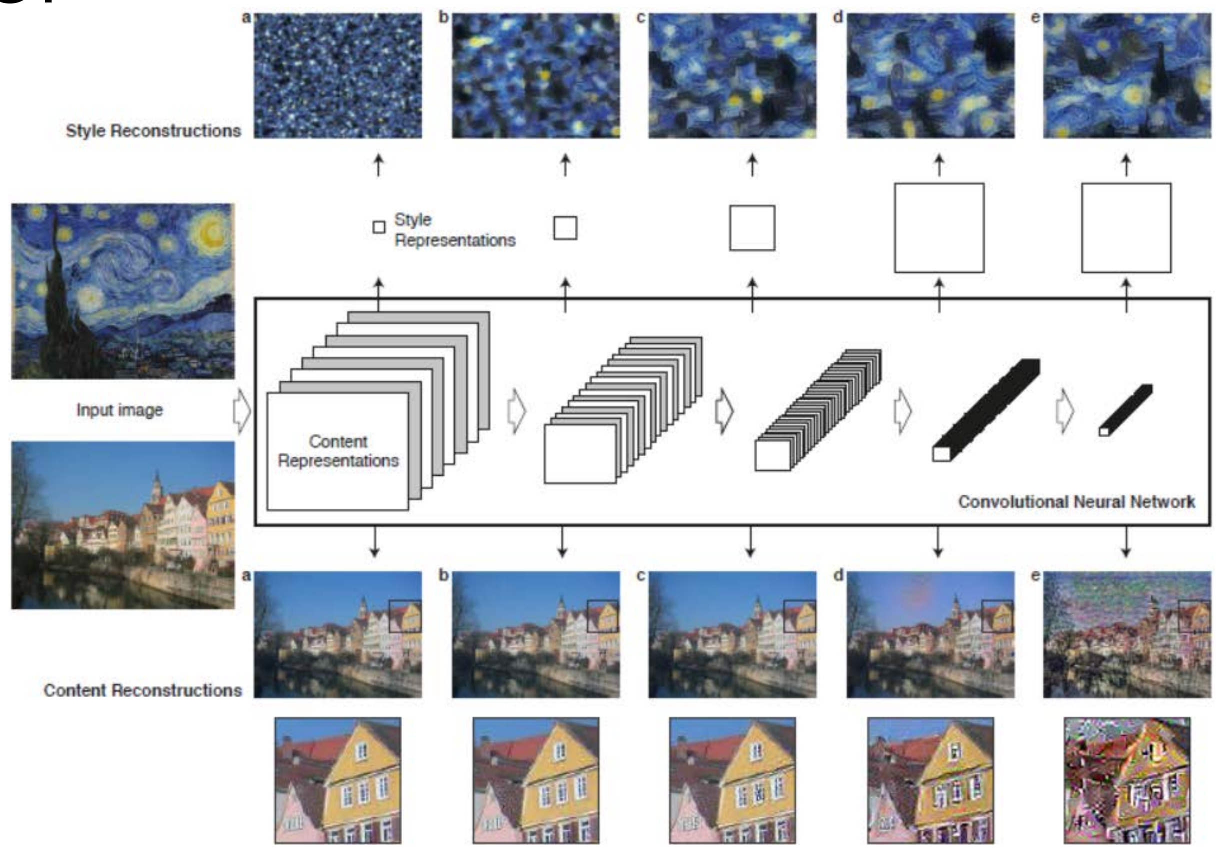


II. Image Style Transfer

E. Image Style Transfer

E1. 1st Trial [2015, Gatys]

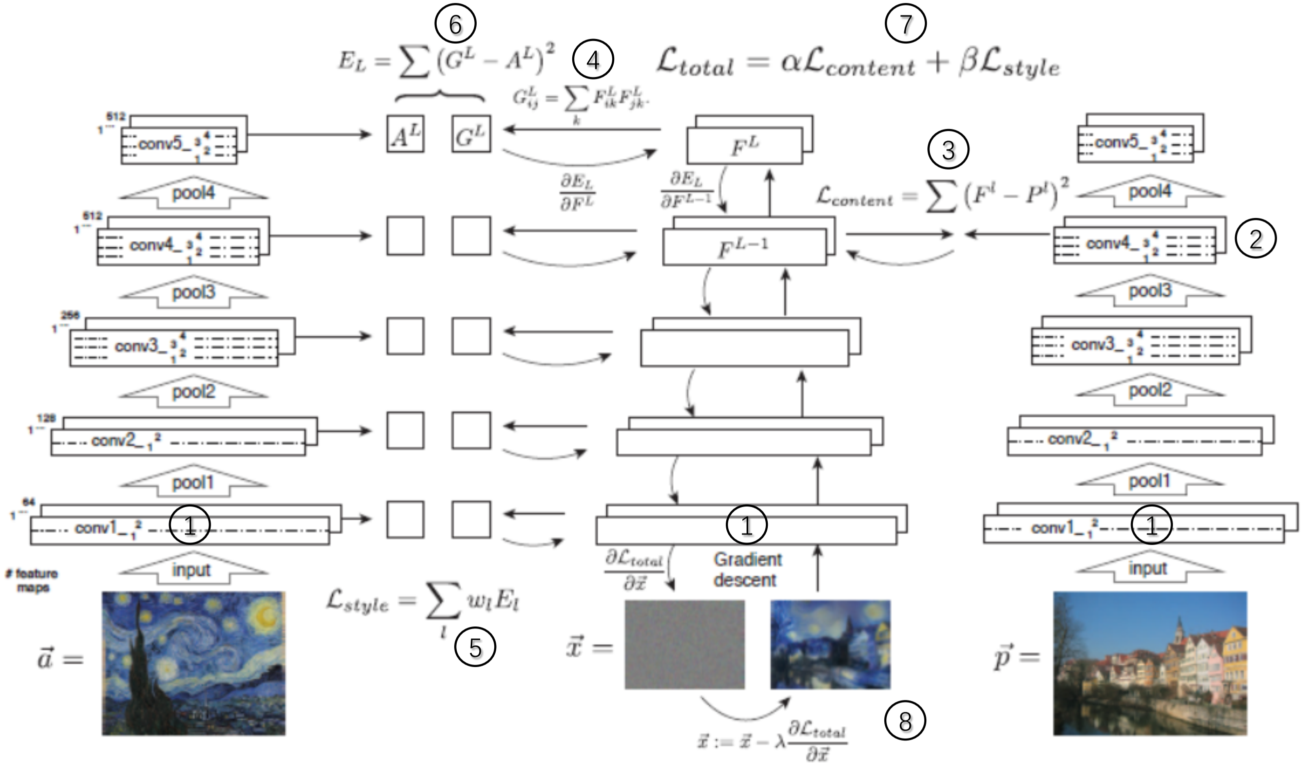
- **Questions:**
  - How to represent contents?
  - How to represent styles?
  - How to minimizing the gap?
  - How to combine content / style?



II. Image Style Transfer

E. Image Style Transfer

E1. 1st Trial [2015, Gatys]

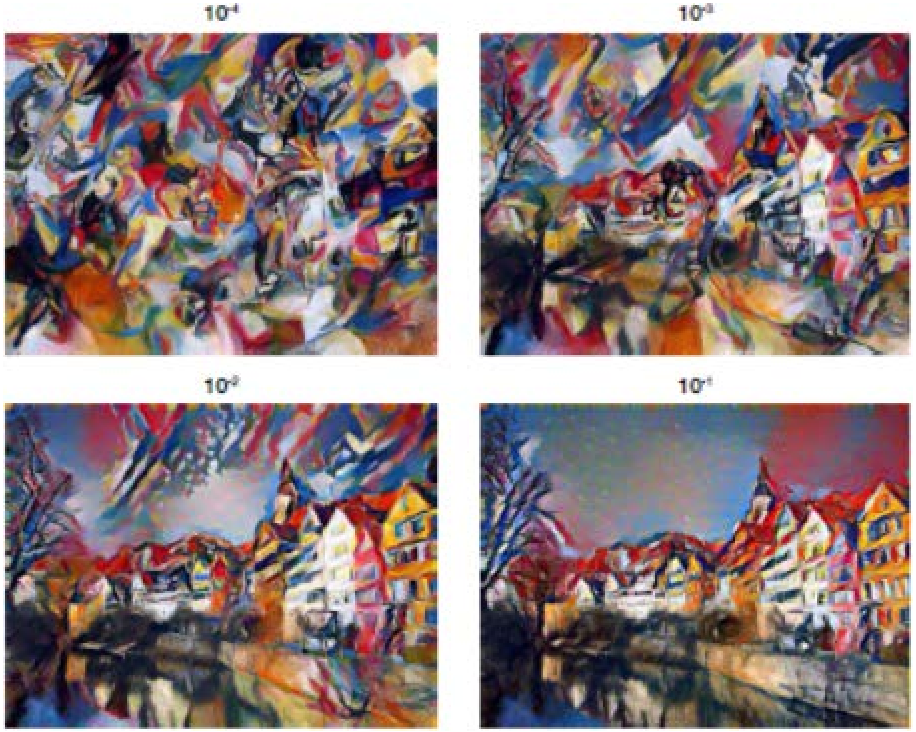


1. Vgg. Same network.
2. Higher layer, ampler content info.
3. Content loss
4. Style representation: Gram Matrix
5. Different weights for different styles of different layers
6. Style loss
7. Combine contents and styles
8. Generated from white noise

II. Image Style Transfer

E. Image Style Transfer

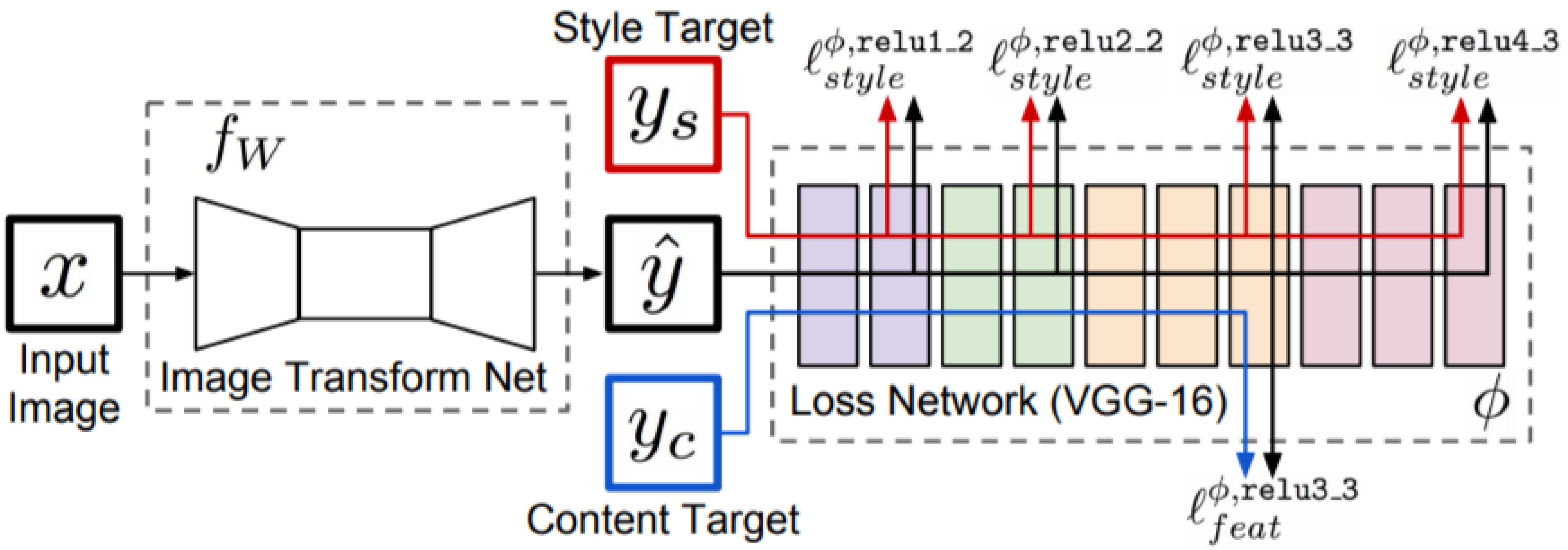
E1. 1st Trial [2015, Gatys]



II. Image Style Transfer

E. Image Style Transfer

E2. Make It Faster! [2016, Perceptual Loss, Justin]



II. Image Style Transfer

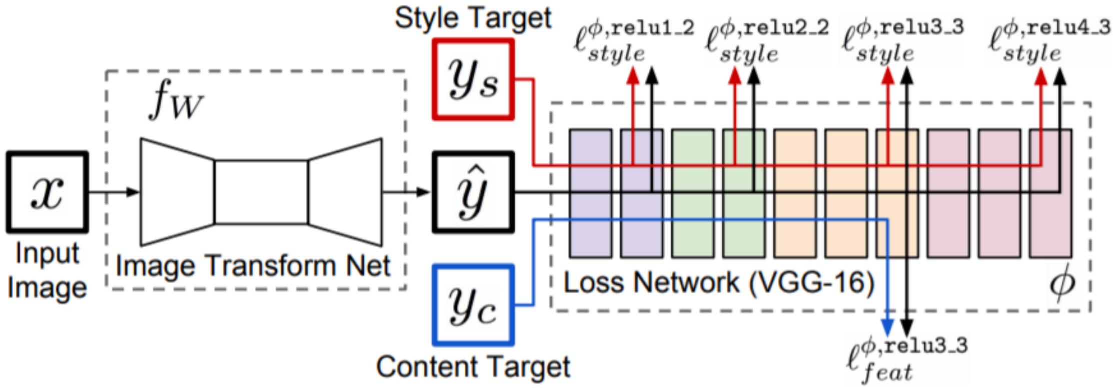
E. Image Style Transfer

E2. Make It Faster! [2016, Perceptual Loss, Justin]

- **Import aspects:**
  - Perceptual Loss! Perceptual Loss! Perceptual Loss!
  - Variation Regularization

$$\hat{y} = \arg\min_{y} \lambda_c \ell_{feat}^{\phi,j}(y, y_c) + \lambda_s \ell_{style}^{\phi,J}(y, y_s) + \lambda_{TV}\ell_{TV}(y)$$

  - Functional network + Loss network



II. Image Style Transfer

E. Image Style Transfer

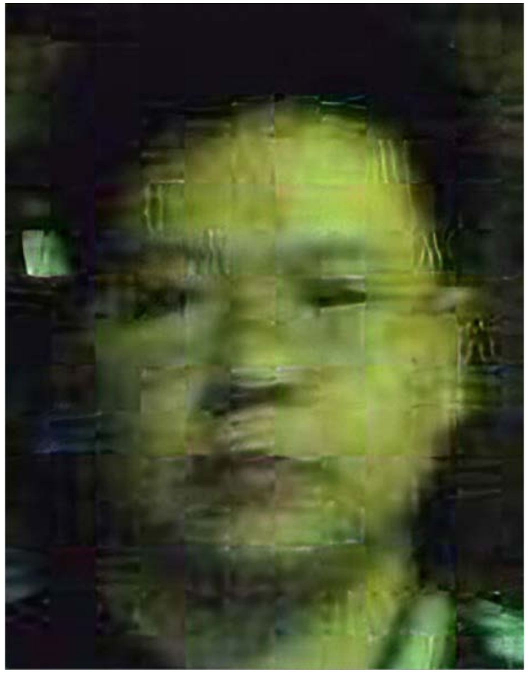
E2. Make It Faster! [2016, Perceptual Loss, Justin]

- **Tips:**
  - **L1 / L2 / Perceptual / Gradient loss in Image Transferring**

    L1: Good for details but bad for color
    L2: Good for color but bad for details
    Perceptual: Good for everything. Common in super resolution
    Gradient: Can decrease chessboard pattern tremendously

- **Thinking:**

  Assume your task is to improve the rate of face recognition under bad light condition.
  What can you do?



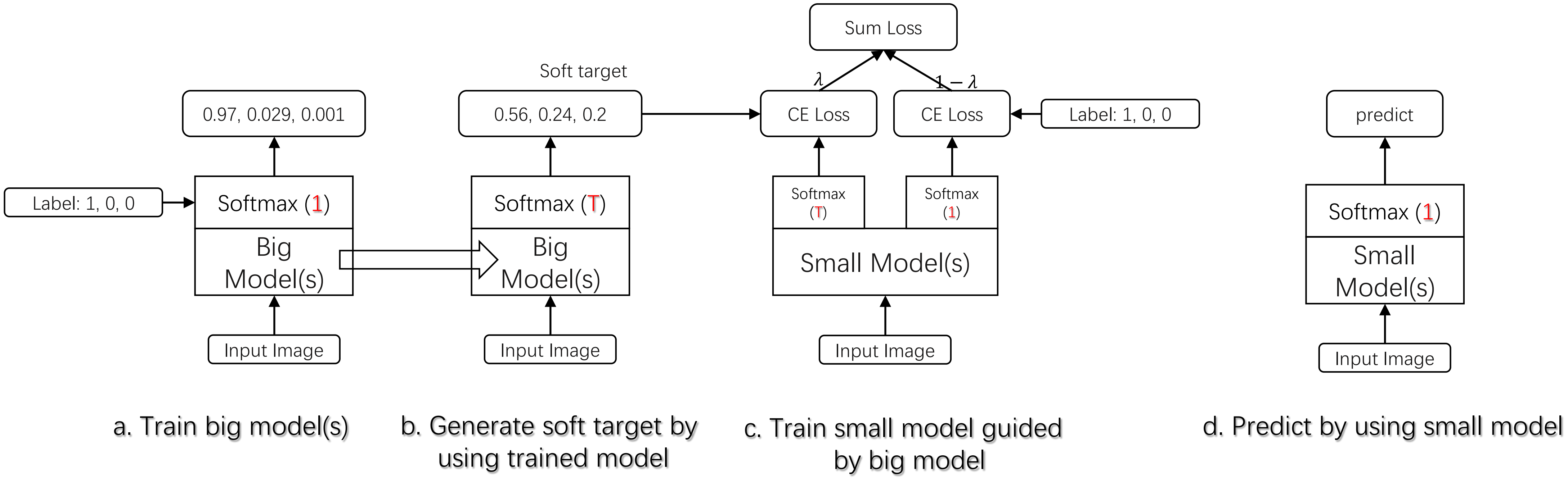
II. Image Style Transfer

F. Feature mimicking / Model distillation

- **Aim:**
  - Distill knowledge from bigger models
  - Use the distilled knowledge to guide the learning of smaller models
  - Use smaller models to mimic the effect of bigger models
- **Papers:**
  - Distilling the Knowledge in a Neural Network [2015, Hinton]
  - FitNets: Hints for Thin Deep Nets [2015, Remero, Bengio]
  - Mimicking Very Efficient Network for Object Detection [2017, Quanquan Li]

II. Image Style Transfer

F. Feature mimicking / Model distillation



III. Other Applications

III. Other Applications

G. Others

- Image Enhancement [2018]

Channel split;

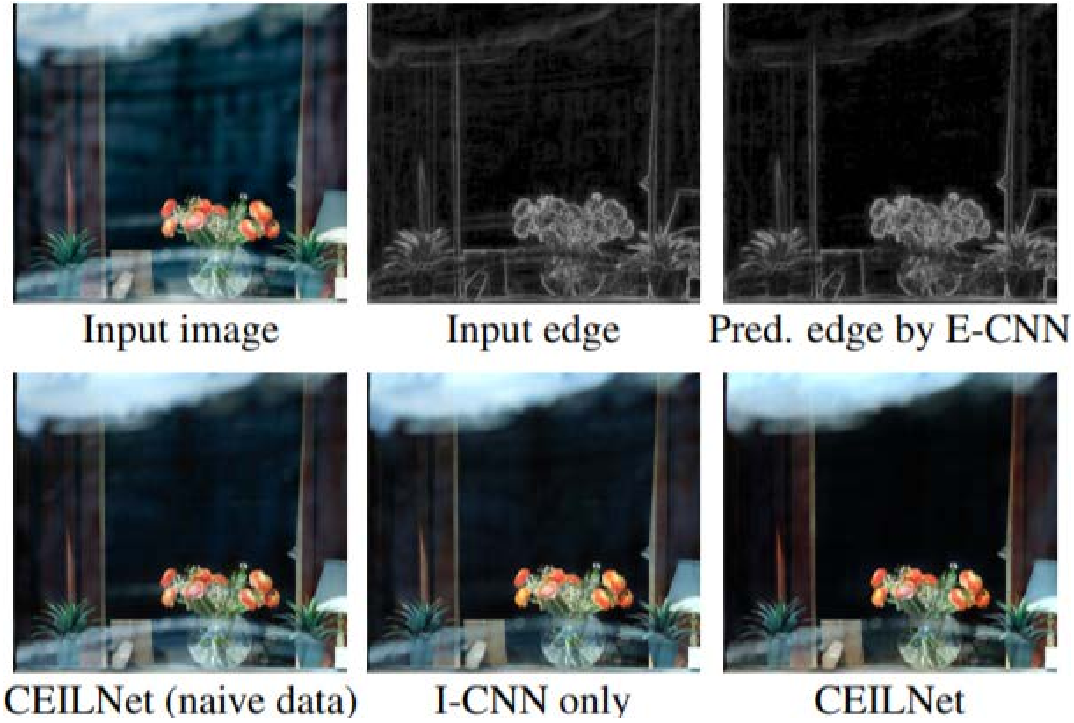
Exposure combination;

High/Low frequency split

III. Other Applications

G. Others

- Reflection Removal [2018]



$$\mathbf{I} = \mathbf{B} + \mathbf{R}$$

III. Other Applications

G. Others

- Super Resolution