Queen Mary University of London
Science and Engineering

QMUL-BUPT Joint Programme
JP Student Innovation Centre
Annual Showcase **2021/22**

RU-Net : Solar Panel Detection From Remote Sensing Image

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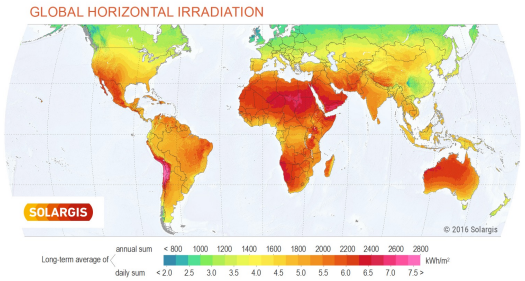
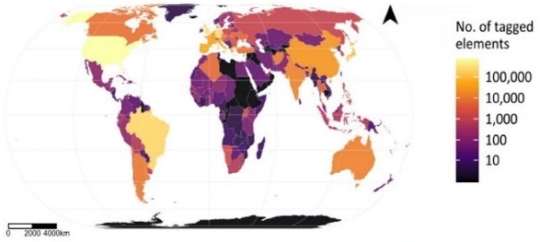
INTRODUCTION

—— literature review of solar energy and image segmentation





Solar Energy& Solar panel distribution

Solar panel detection

Power plant

Residual areas

Detection& segmentation method

Shallow features

Threshold segmentation

Edge detection Segmentation

Region Segmentation

Middle features

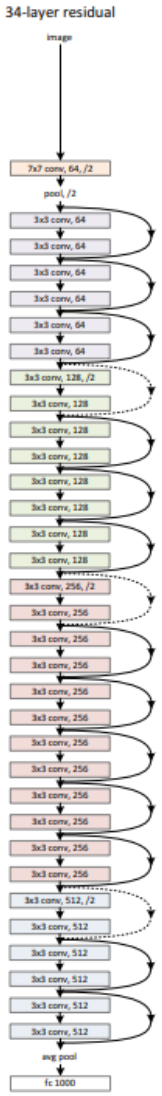
Clustering Segmentation

MRF Segmentation

Deep features

DeepSolar FCN,U-NET

MODEL: RU-Net



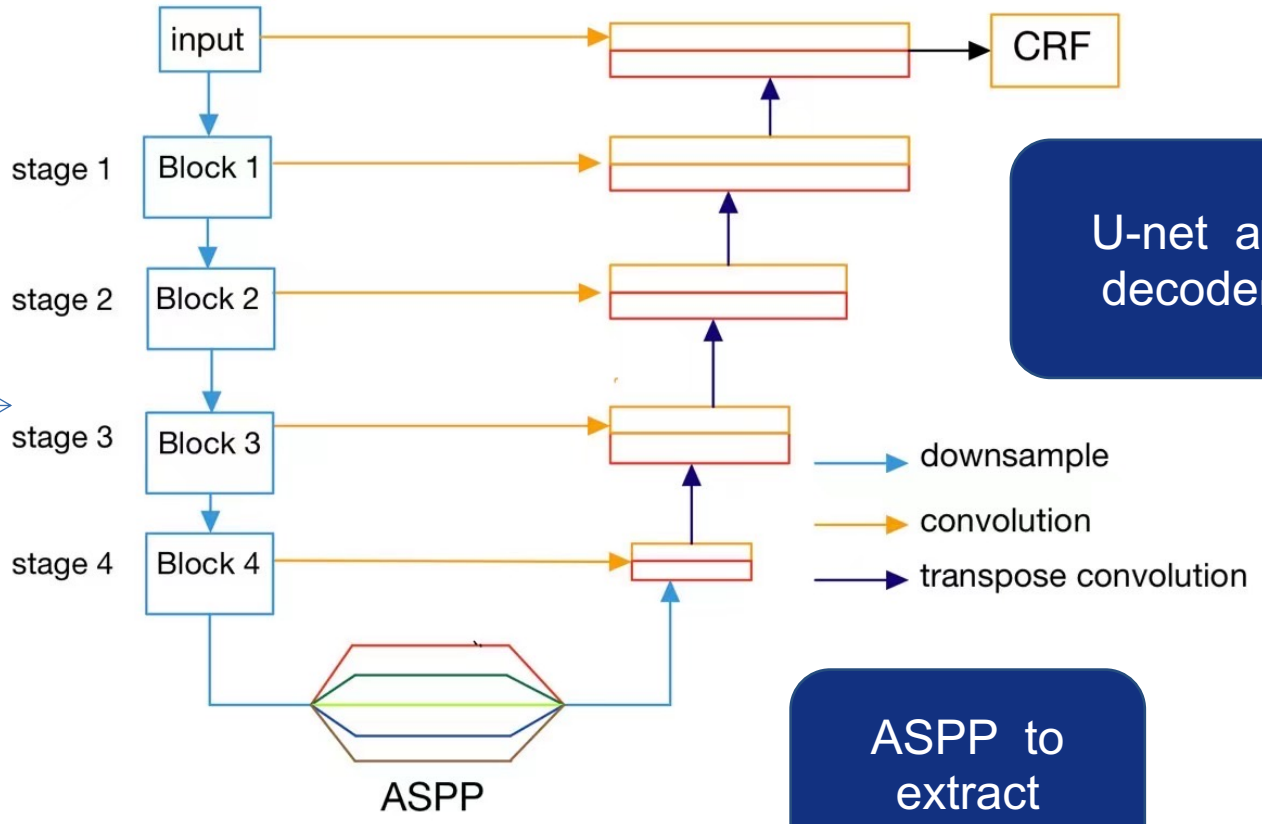
ResNet 34 as pretrained model

remove avgPool

&sigmoid

ResNet 34 as encoder

——model overview



U-net as decoder

Atrous Spatial Pyramid Pooling

ASPP to extract features

MODEL: RU-Net

——Classification/Segmentation: ResNet34

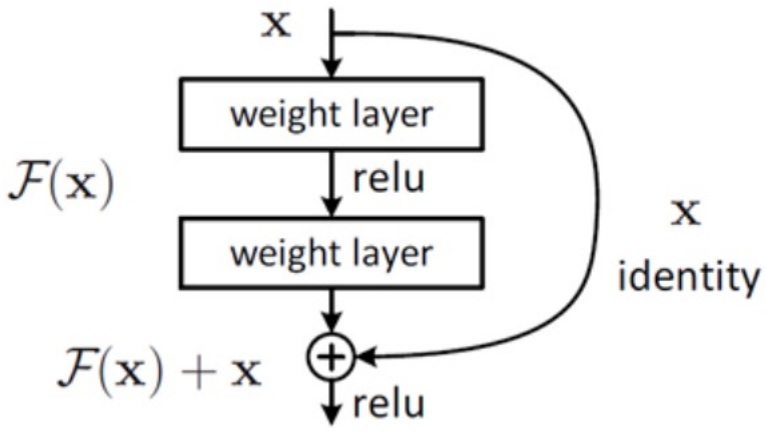
ResNet 34 :

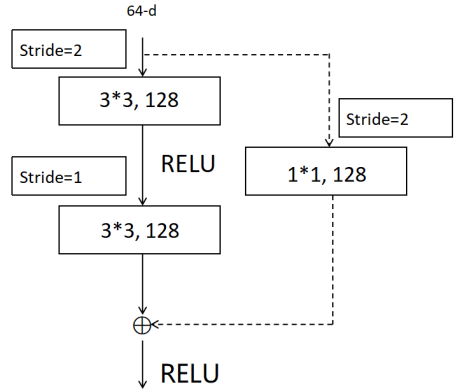
1.avoid degradation 2.no vanishing gradient

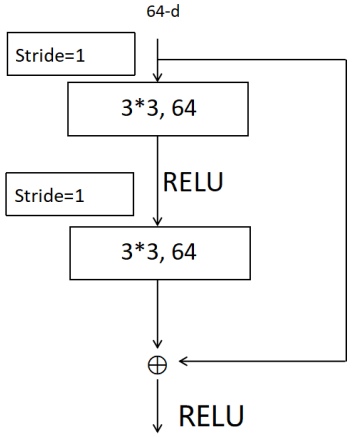
H(x) = F(x) + x

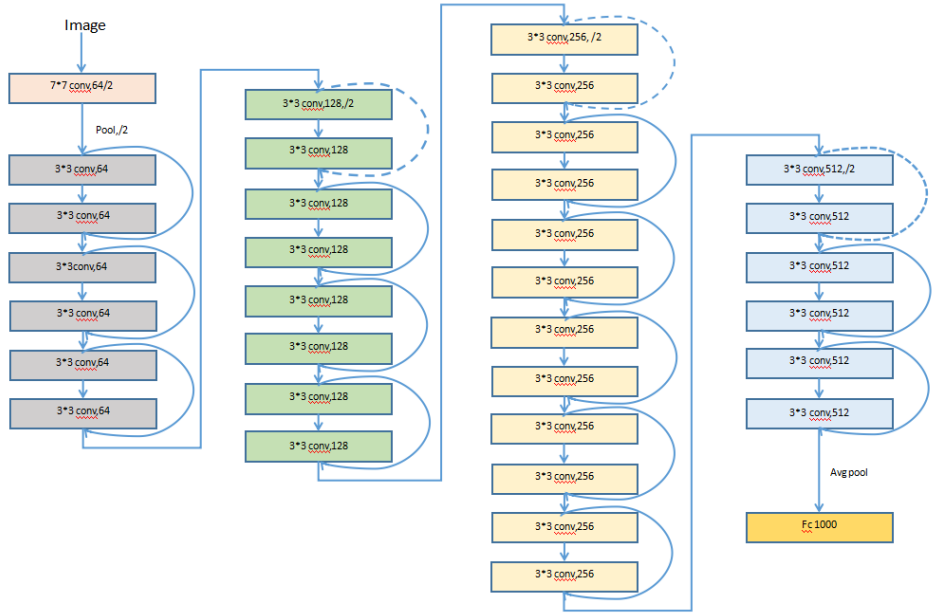
$$x_L = x_l + \sum_{i=l}^{L-1} F(x_i, W_i)$$

$$\frac{\partial \varepsilon}{\partial x_l} = \frac{\partial \varepsilon}{\partial x_L}\frac{\partial x_L}{\partial x_l} = \frac{\partial \varepsilon}{\partial x_L}\left(1 + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-1} F(x_i, W_i)\right)$$





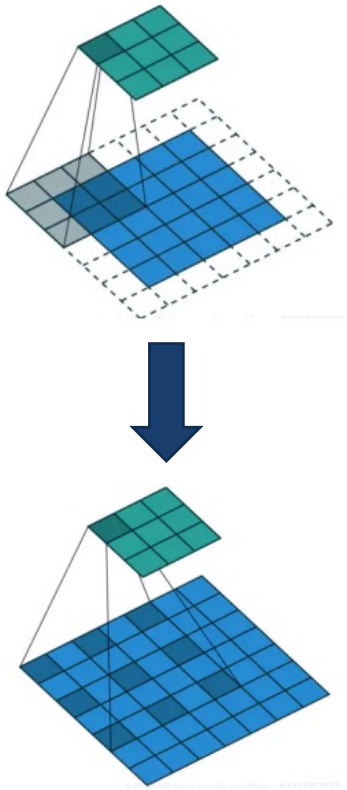




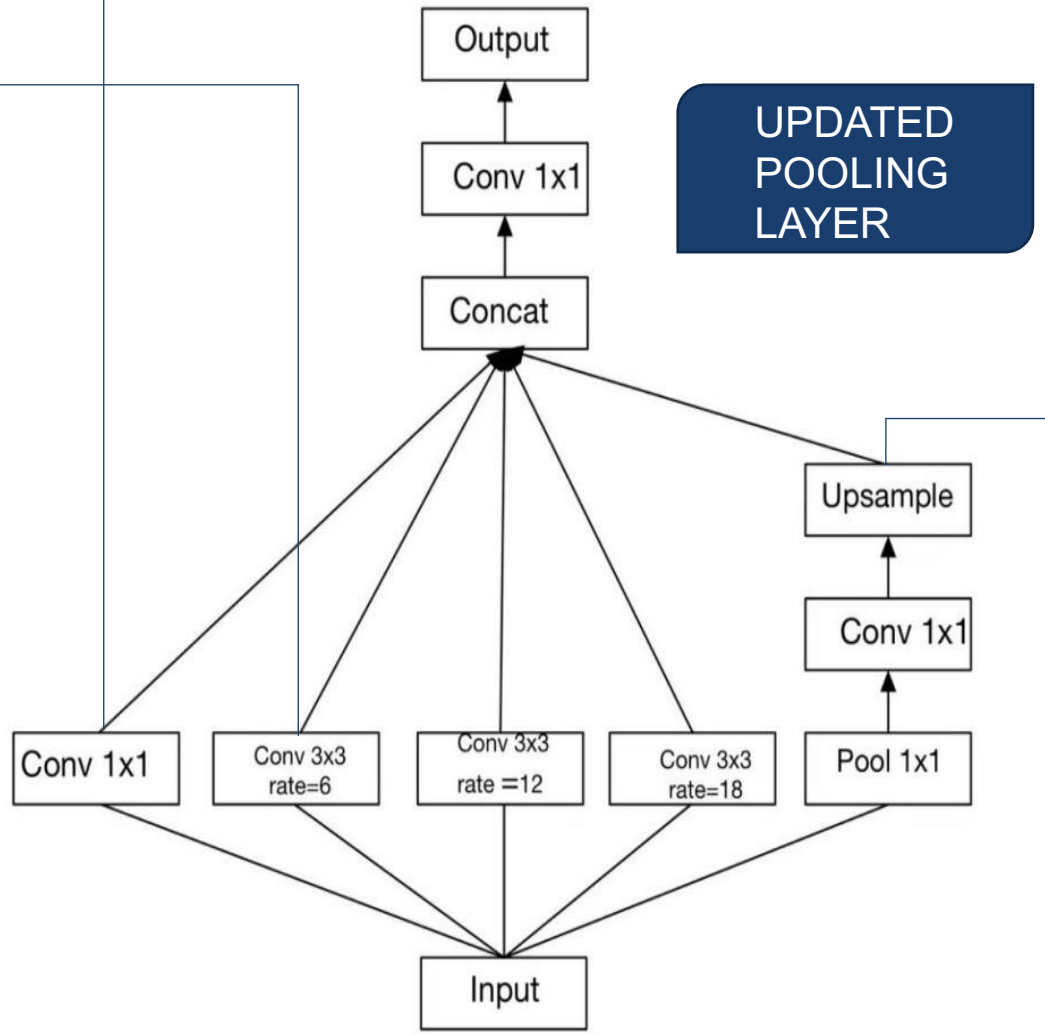
MODEL: RU-Net

Atrous convolution

User defined multi-dimension extraction



——Aatrous Spatial Pyramid Pooling(ASPP)



conv 1*1

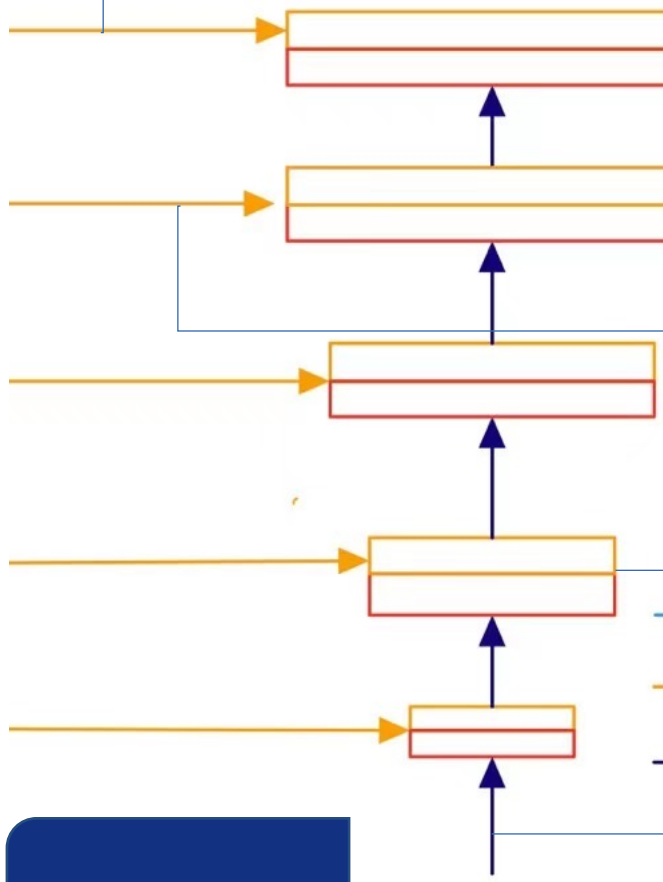
Reduce dimension of features
Reduce amount of computation

Self-adaptive pooling

Calculate kernel size and stride automaticaly
Avoid over-fitting

MODEL: RU-Net

—segmentation : U-net



DECODER

HOOK

Save features inside network without changing the structure

Convolution

Change the dimension from encoder to decoder

Concatenation

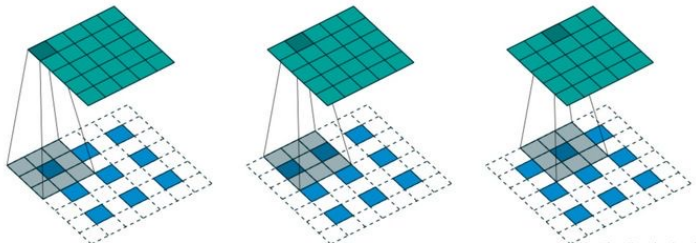
Different from addition in FCN, concatenation does not lose any features

downsample

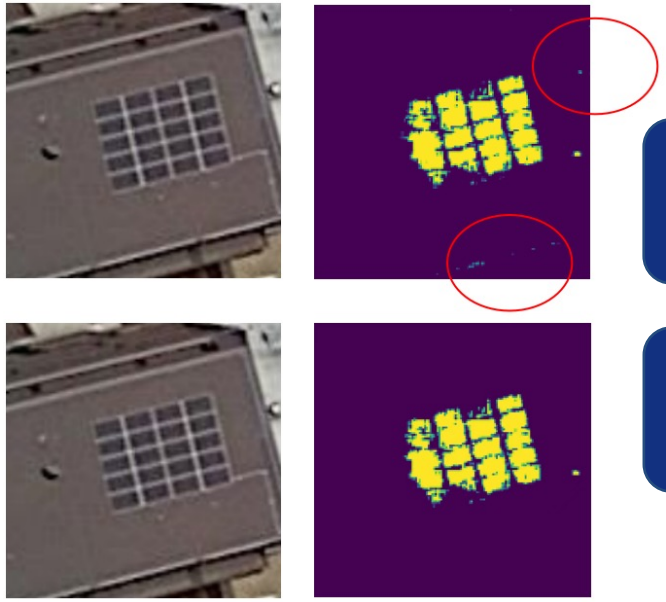
convolution

transpose convolution

Transpose conv



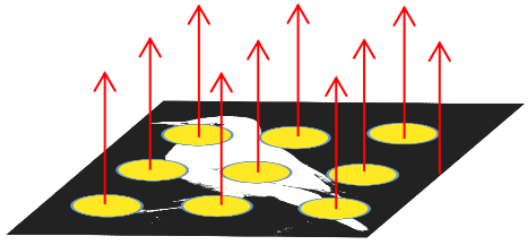
MODEL: RU-Net



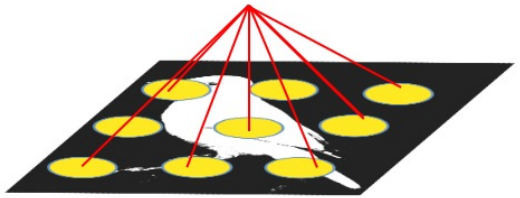
eliminate FP

smoother edge

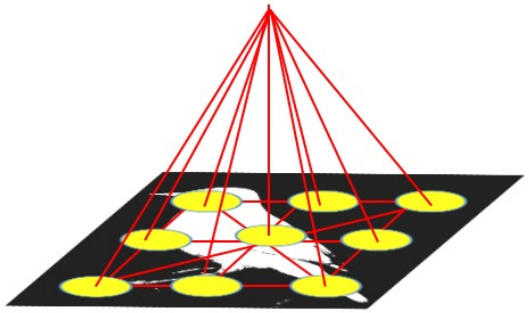
——post-process : Dense-CRF



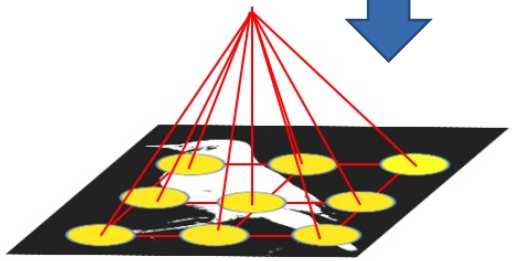
Classified by its own pixel



Classified by surroundings(not related)



Dense-CRF: Classified by rest part(related)



CRF: Classified by surroundings(related)

Markov property

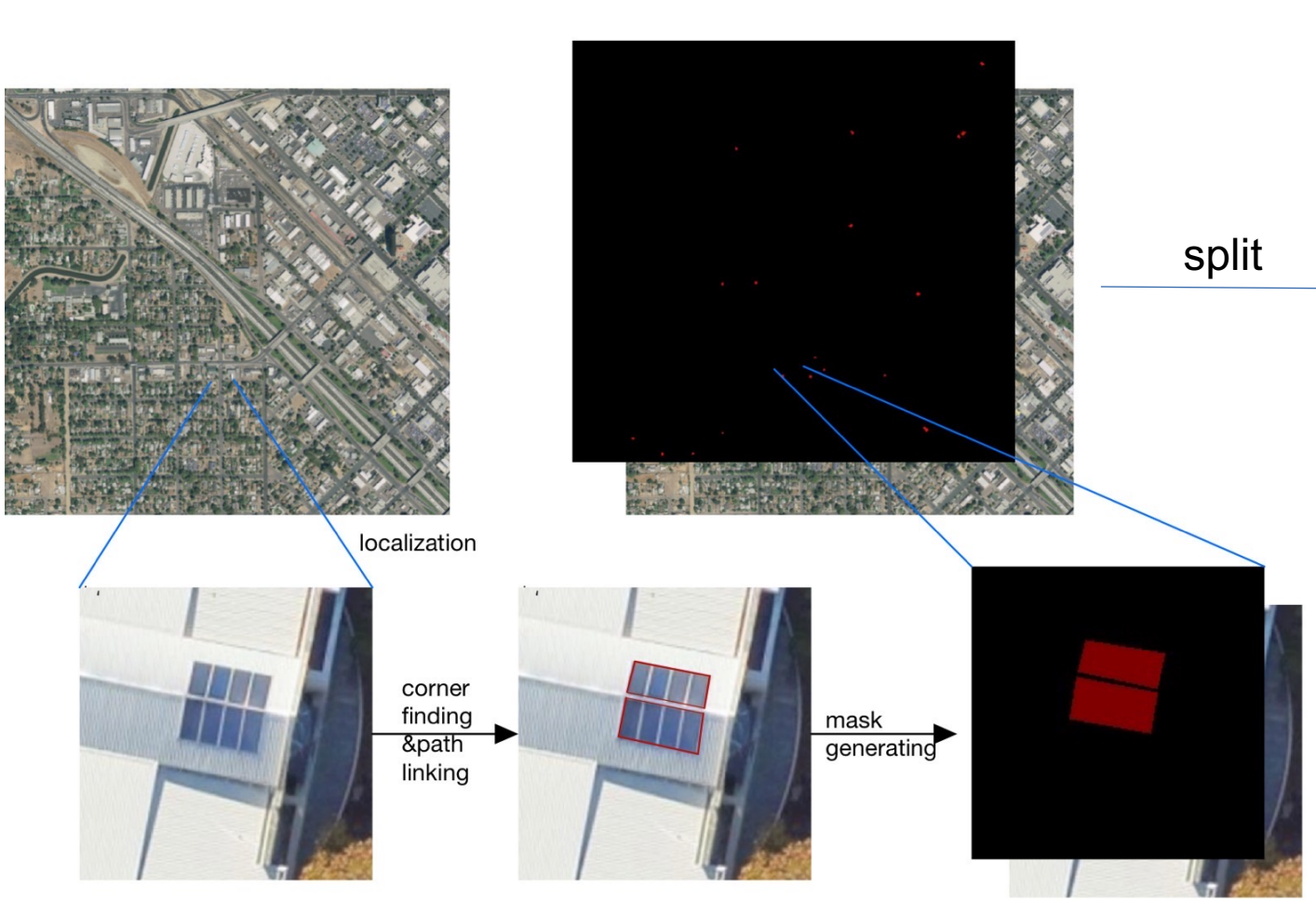
$$P(Y_v|Y_w, w \neq v) = P(Y_v|Y_w, w \sim v)$$

Condition random field

X,Y are random variable , P(Y|X) is condition probabiity distribution, if Y has Markov property, then P(Y|X) is CRF.

DATA SET: Remote Sensing Image

——Data set preparation and preprocessing



Distributed Solar Photovoltaic Array Location and Extent Data set for Remote Sensing Object Identification

- High resolution
- Metadata
- Large(50 G)

EXPERIMENTS

*Based on Distributed Solar Photovoltaic Array Location and Extent Data set for Remote Sensing Object Identification

*Baseline is the proposed method(ResNet-ASPP-Unet)

1.Experiments of upsample(transpose convolution and linear interpolation,based on Res-ASPP-Unet)

name	IOU	Recall	Precision
transpose convolution	**83.5%**	**94.5%**	**95.6%**
linear interpolation	82.9%	93.8%	94.3%

2. Experiments of loss function(Cross Entropy Loss, Focal Loss, Dice Loss)

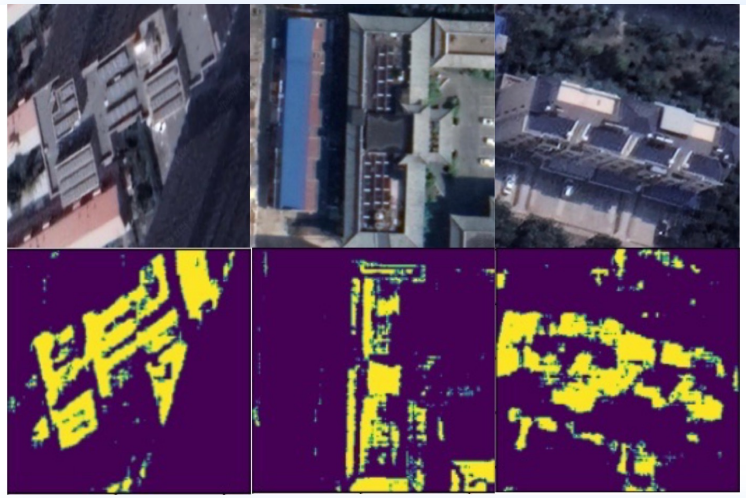
name	IOU	Recall	Precision
Cross Entropy Loss	**83.5%**	**94.5%**	**95.6%**
Focal Loss	82.1%	92.2%	93.1%
Dice Loss	81.4%	89.9%	90.6%

EXPERIMENTS

3.Experiments of models

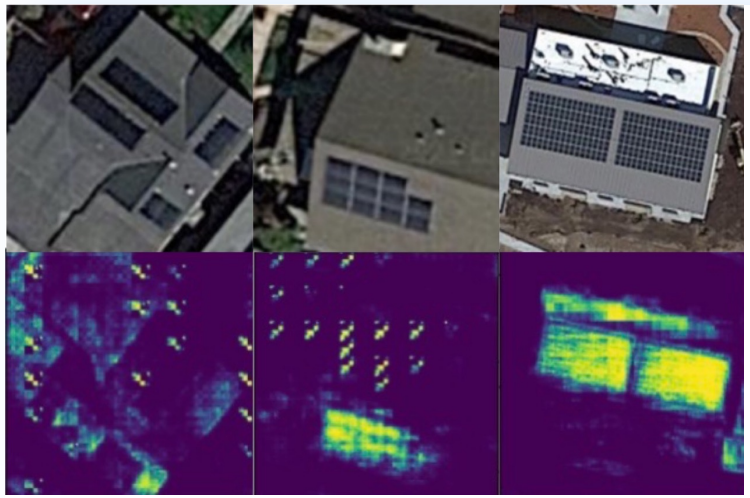
name	precision	recall	IOU
FCN	84.4%	83.9%	74.9%
U-net	82.5%	81.7%	73.7%
Deepsolar	93.1%-93.7%	88.5%-90.5%	78.3%
Resnet-Unet	93.6%	92.2%	0.796(0.805 with CRF)
Res-ASPP-Unet	**95.6%**	**94.5%**	**0.835(0.840 with CRF)**

EXPERIMENTS



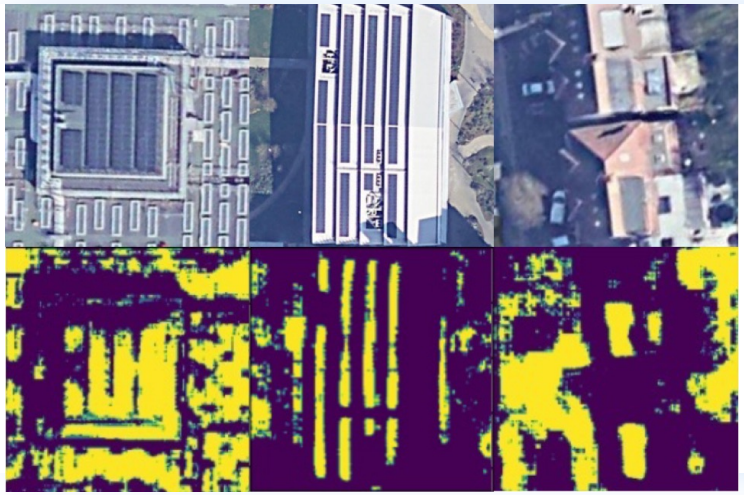
North of China

Complex rooftop



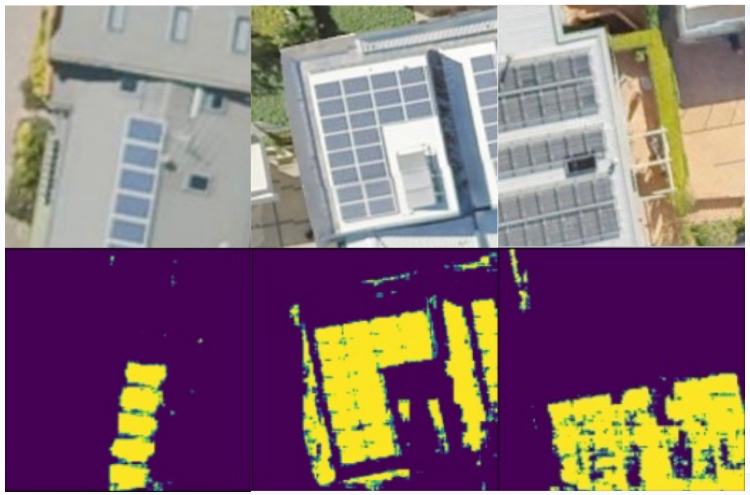
Florida

Low resolution



London

Cloudy weather



Sydney

Bright

Simple environment

Demo Presentation

CONCLUSION&FURTHER WORK

Conclusion & Innovation

1.Enhanced Solar panel detection&segmentation model

2.Better performance in low pixel images

Further work

1.Small size solar panel detection

2.End-to-end algorithm

Thanks
For Watching