# Gated Convolutional Neural Network for Semantic Segmentation in High-Resolution Images

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UFMG

# Introduction

- High resolution images contains a lot of complex objects with various sizes

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[1] 2014 IEEE GRSS Data Fusion Contest.
Online:http://www.grss-ieee.org/community/technicalcommittees/data-fusion/

# Introduction

- Many objects in this image have high intra-class variance and low inter-class variance. (Grey roofs and roads, for example)

2

[2] 2014 IEEE GRSS Data Fusion Contest.
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# Introduction


- Features at different levels need to be extracted and jointly combined to fulfill the segmentation task
- High level and abstract features are more suitable for large and confused objects
- While small objects benefit from low-level and raw features
- In traditional way, we only use high-level features and the low-level feature maps are discarded

# Introduction

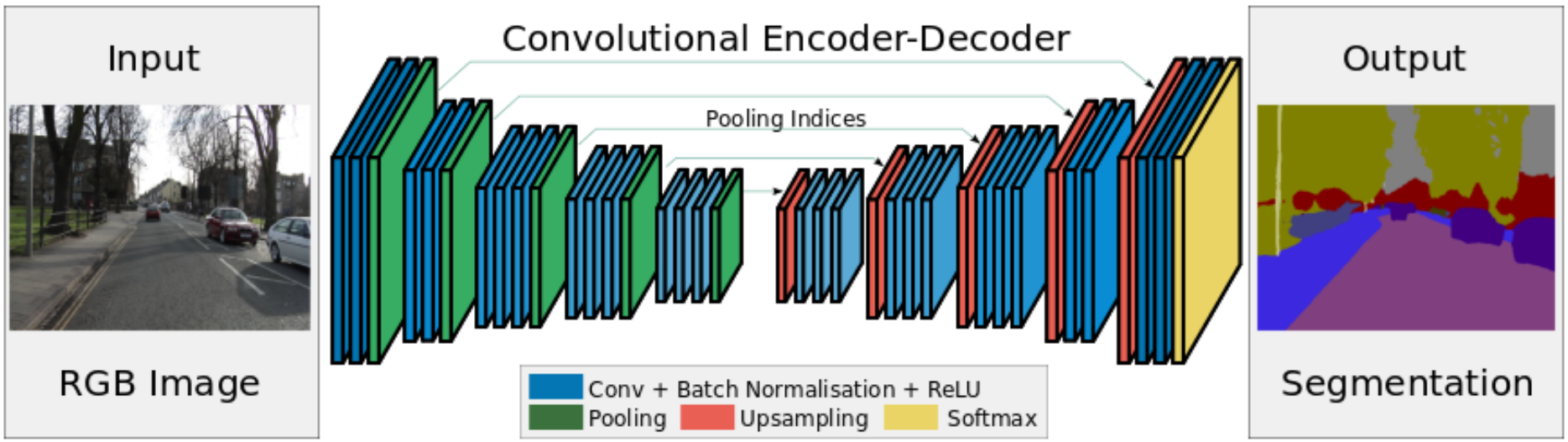


**Figura :** Segnet

[3].

[3] Vijay Badrinarayanan, Alex Kendall e Roberto Cipolla. "Segnet: A deep convolutional encoder-decoder architecture for image segmentation". Em: *arXiv preprint arXiv:1511.00561* (2015).

# Introduction

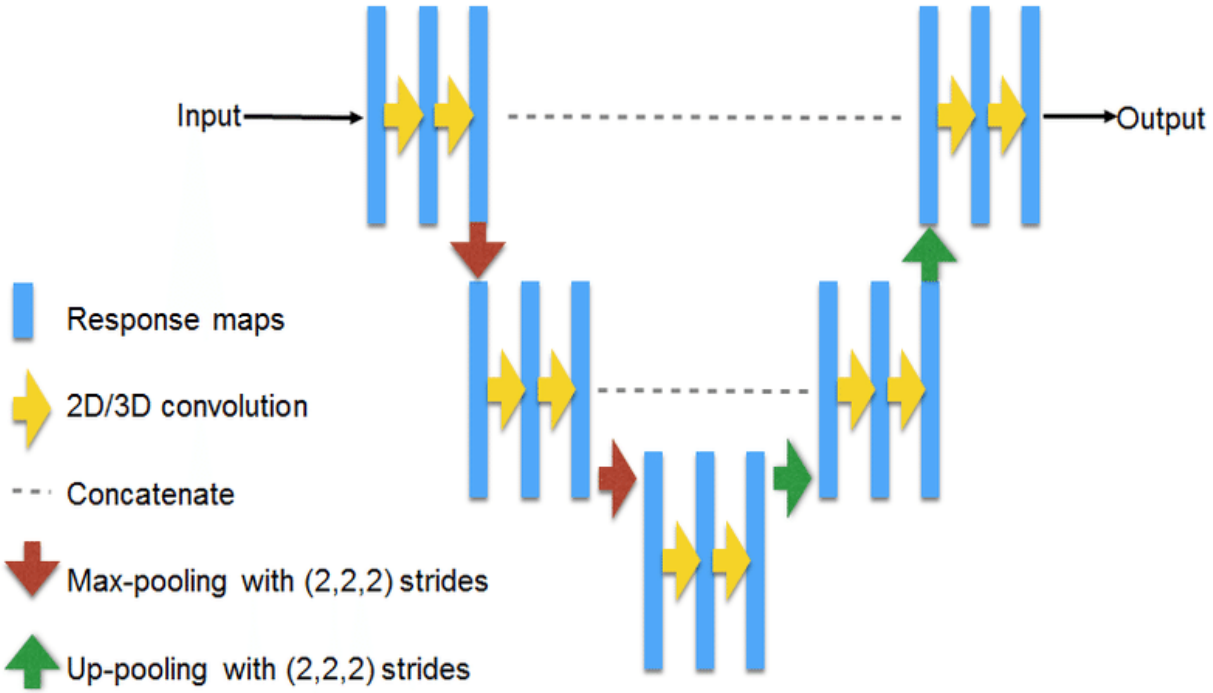


**Figura :** UNet

[4] Olaf Ronneberger, Philipp Fischer e Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation". Em: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer. 2015, pp. 234–241.

# Introduction


Without feature selection:

- Redundant information can result in oversegmentation when the model tends to receive more information from lower layers
- Fine-grained details can be lose and lead to under-segmentation when the networks tens to receive more information from upperlayers

# Introduction

## Hypothesis


- Is using all the features really the best alternative?

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- Is using all the features really the best alternative?
  - If no. How to make a selection?

# Introduction

## Entropy


- Generally, entropy refers to disorder or uncertainty

$$H(x) = E[-log_2(p_i(x))] = -\sum_{i=1}^{k} p_i(x) log_2(p_i(x)) \quad (1)$$

where:

$E[.]$ denotes expectation over all the k categories
$p_i(x)$ is the probability of pixel x belonging to category i

# Introduction

## Entropy


P(x) = [0.8,0.1,0.1] $\quad log_2 0.8 = -0.3219 \quad log_2 0.1 = -3.3219$

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$$H(x) = 0.9219$$

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## Entropy

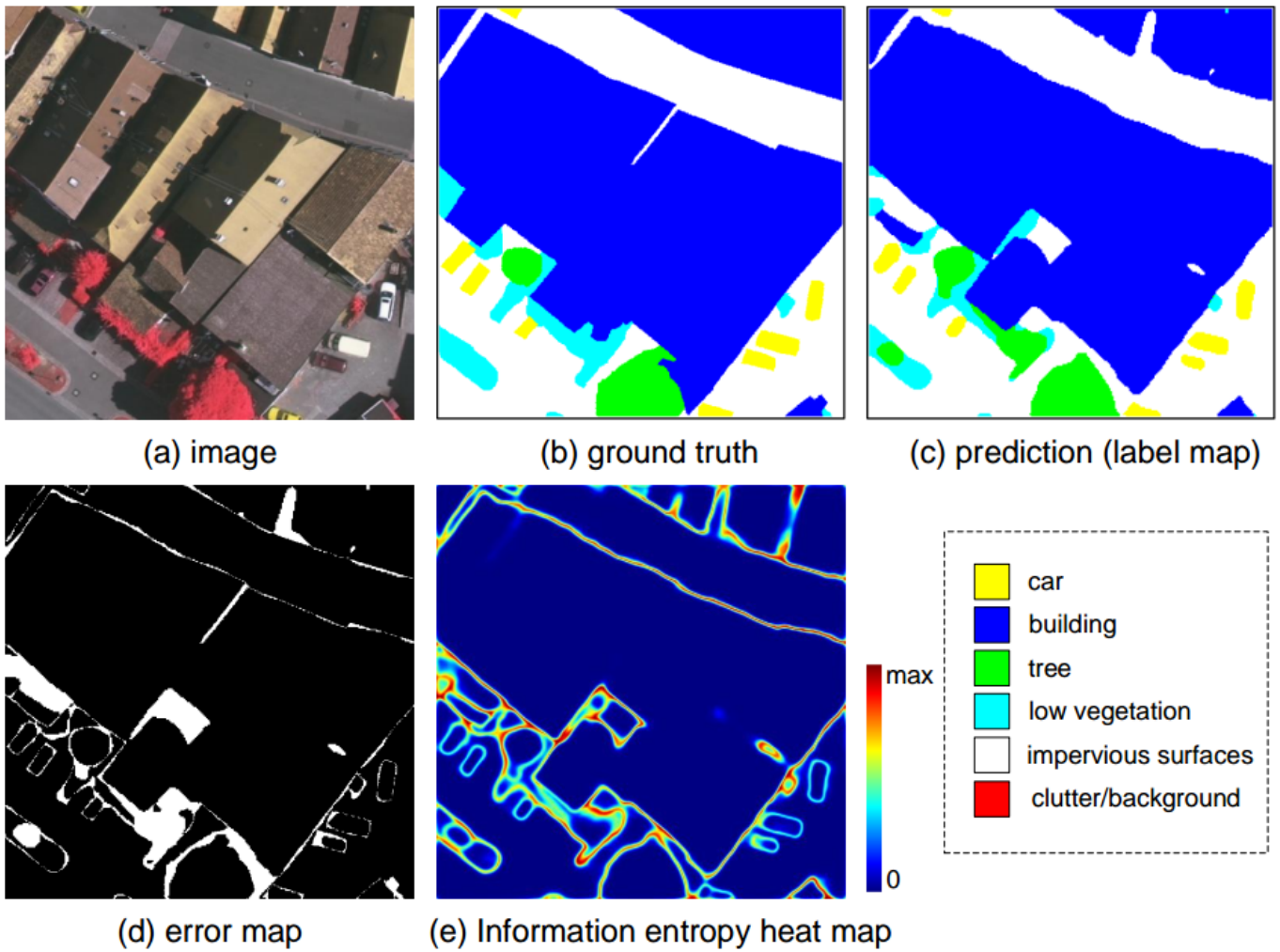

P(x) = [0.8,0.1,0.1] $H(x) = 0.9219$

P(x) = [0.5,0.4,0.1] $H(x) = 1,3601$

P(x) = [0.3,0.3,0.4] $H(x) = 1,5709$

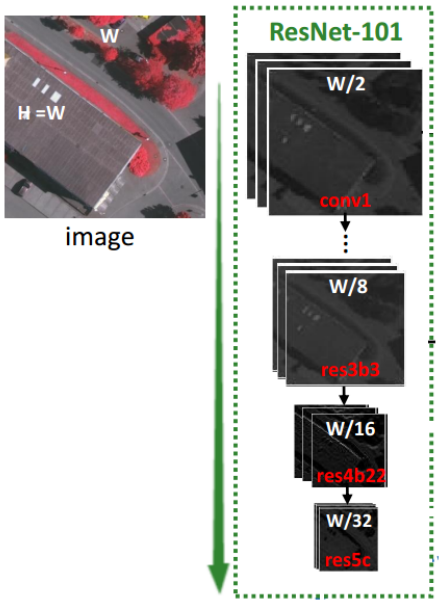
When the entropy of pixel x is maximized p(x) approximates an uniform probability distribution. In this case, the network is unable to classify this pixel using only existing information

# Introduction



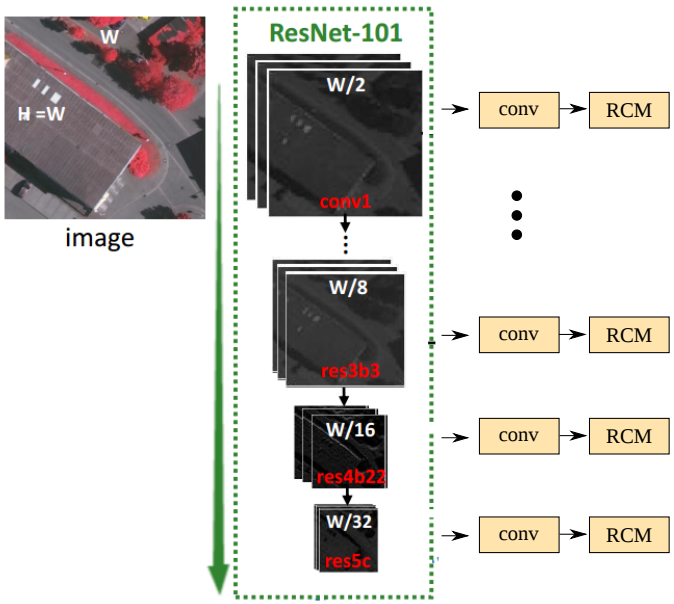
# Approach

- Features are extracted in a pretrained ResNet



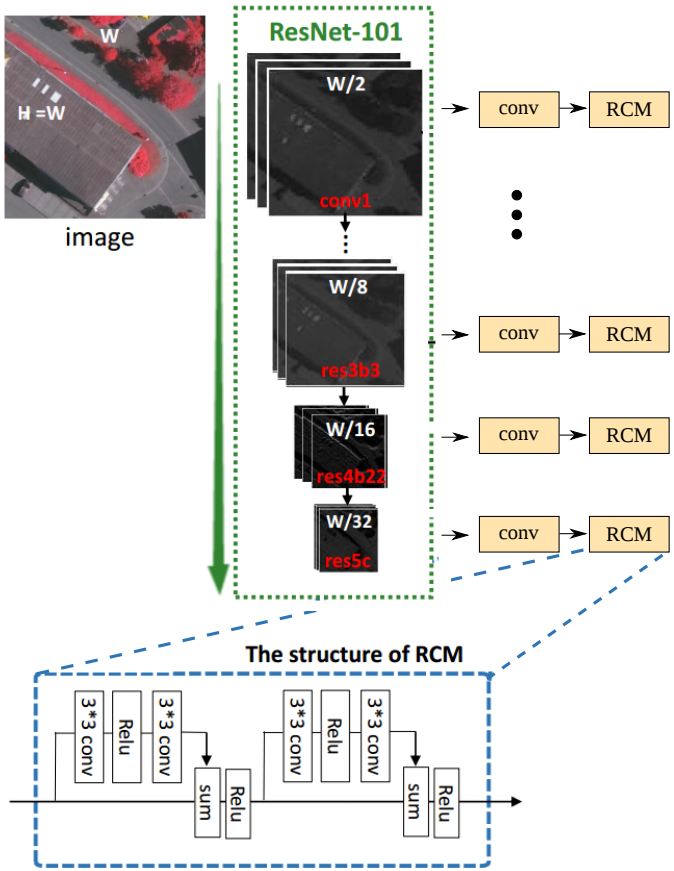
# Approach

- Each set of features is submitted to a convolutional layer followed by a RCM module



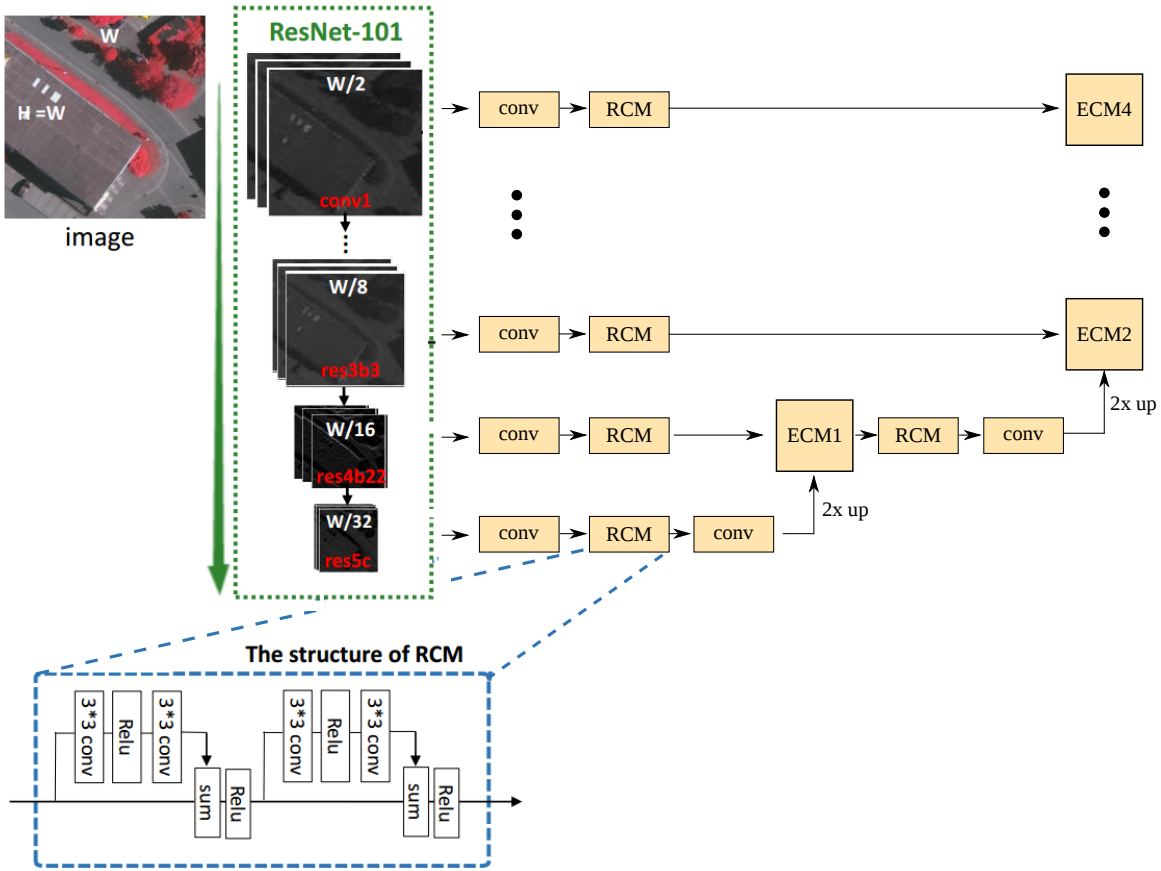
# Approach

- RCM module are based in residual blocks in ResNet and is used to ease the training and avoid the gradient vanishing problem



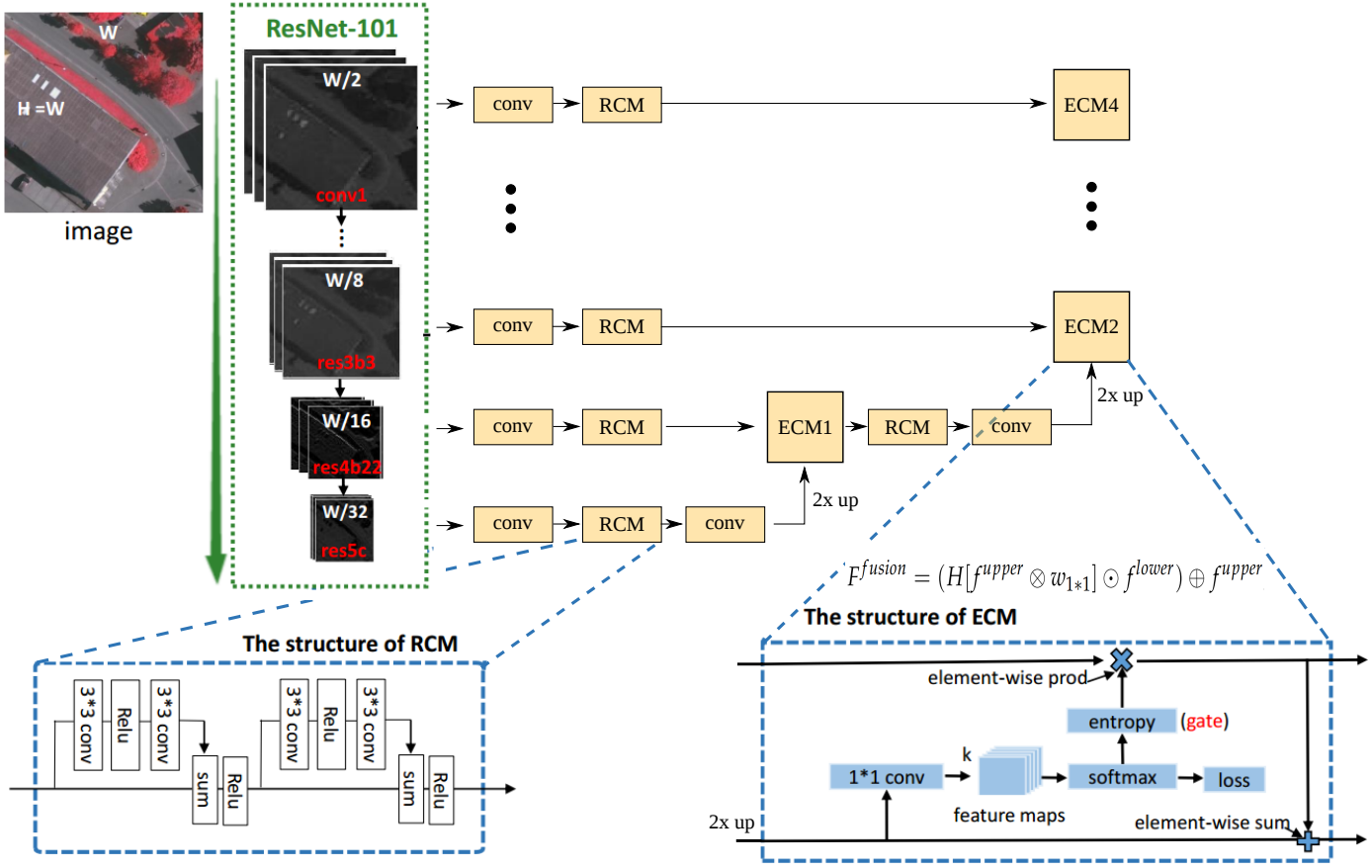
# Approach

- Each pair of output of RCM module is used as input for the ECM module starting from the higher layer until the low layer



# Approach

- The ECM module is used to fuse higher feature maps and low feature maps



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$$F^{fusion} = (H[f^{upper} \otimes w_{1*1}] \odot f^{lower}) \oplus f^{upper}$$

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$$\begin{bmatrix} 0.9219 & 1.3601 \\ 0.9219 & 1.5709 \end{bmatrix} \qquad \begin{bmatrix} 0.2 & 0.8 \\ 0.8 & 0.2 \end{bmatrix} \qquad \begin{bmatrix} 0.4 & 0.6 \\ 0.6 & 0.4 \end{bmatrix}$$

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element-wise product operator

element-wise sum operator

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$$F^{fusion} = \begin{bmatrix} 0.1843 & 1.0880 \end{bmatrix}$$

# Approach

$$F^{fusion} = (H[f^{upper} \otimes w_{1*1}] \odot f^{lower}) \oplus f^{upper}$$

$$F^{fusion} = \begin{bmatrix} 0.9219 & 1.3601 \\ 0.9219 & 1.5709 \end{bmatrix} \odot \begin{bmatrix} 0.2 & 0.8 \\ 0.8 & 0.2 \end{bmatrix} \oplus \begin{bmatrix} 0.4 & 0.6 \\ 0.6 & 0.4 \end{bmatrix}$$

element-wise product operator

element-wise sum operator

$$F^{fusion} = \begin{bmatrix} 0.1843 & 1.0880 \\ 0.7375 & 0.3141 \end{bmatrix} \oplus \begin{bmatrix} 0.4 & 0.6 \\ 0.6 & 0.4 \end{bmatrix} = \begin{bmatrix} 0.5843 & 1.6880 \\ 1.3375 & 0.7141 \end{bmatrix}$$

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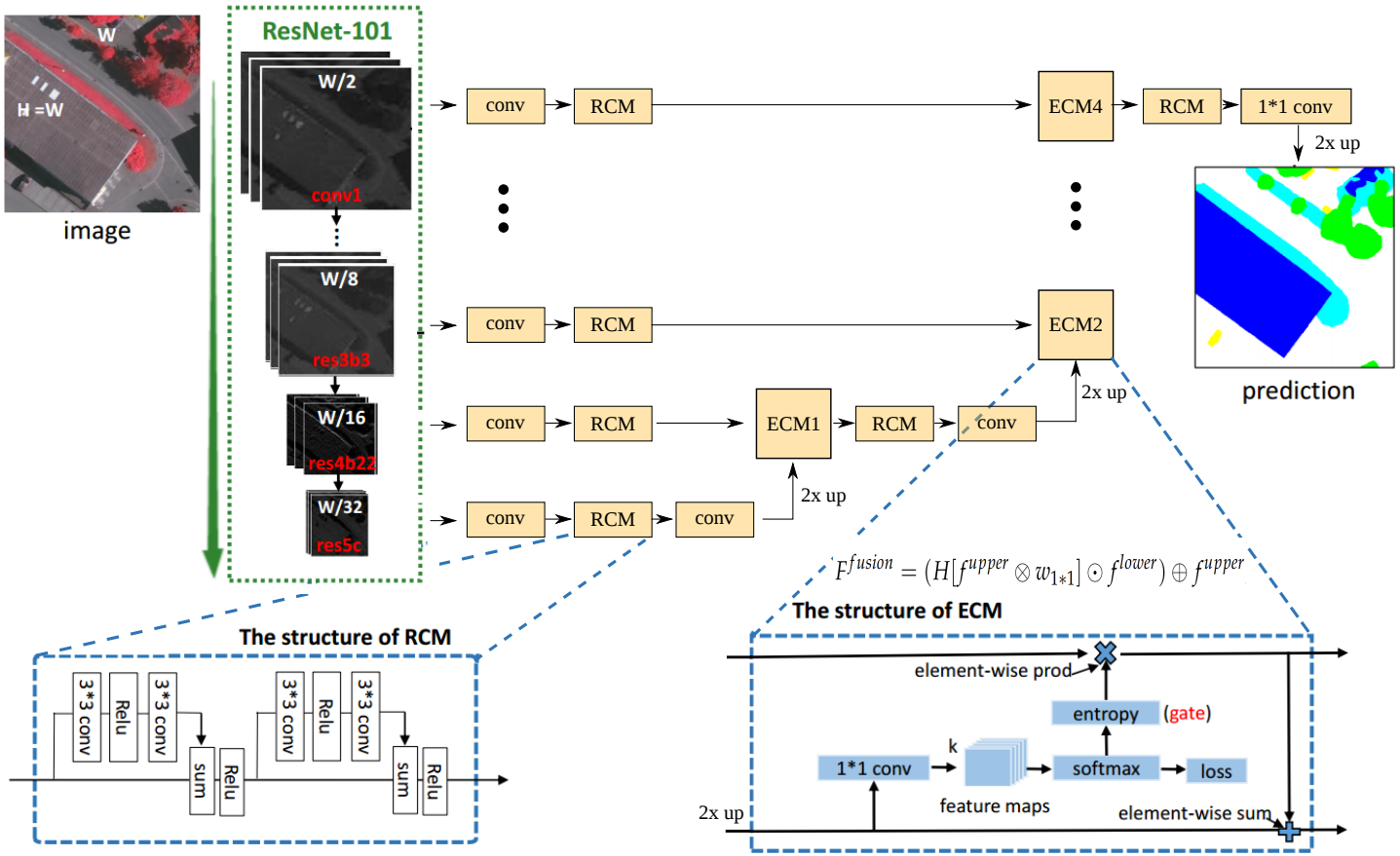
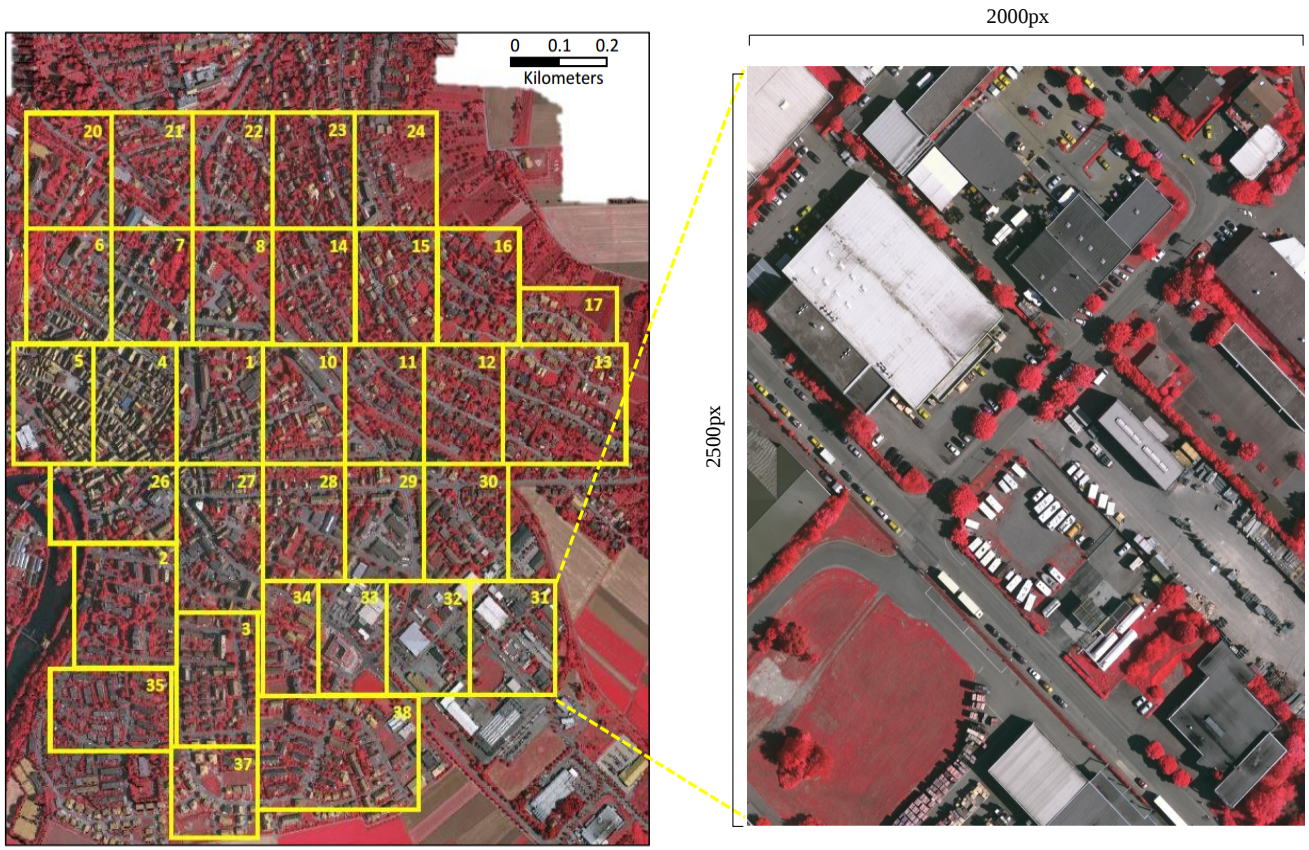
# Approach

- The final architeture is used to classify the test image



# Experimental evaluation

## Dataset




- 16 tiles are used ( 12 for train and 4 for validation)
- Each tile 2500x2000 pixels with 9 cm of resolution
- Manually classified into six classes
- Metrics: F1 score and Overall Accuracy

$$F1 = 2 \times \frac{precision \times recall}{precision + recall}$$

$$precision = \frac{TP}{TP + FP} \qquad recall = \frac{TP}{TP + FN}$$

$$Overall\ Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

TP = true positive
TN = true negative
FP = false positive
FN = false negative

Figure: Overview of the ISPRS 2D Vaihingen Labelling dataset. There are 33 tiles. Numbers in the figure refer to the individual flag.

# Experimental evaluation


- Baseline - GSN without entropy control module
- GSN\GSN_noL - GSN with\without auxiliary loss in ECM, respectively
- GSN_w - classes with different weigths
- GSN_w_ mc - with sliding window overlap and multi-scale input

| Method | Imp Surf | Building | Low_veg | Tree | Car | Overall Accuracy | Mean $F_1$ Score |
|---|---|---|---|---|---|---|---|
| baseline | 87.6% | 93.2% | 73.3% | 86.9% | 54.1% | 86.1% | 79.0% |
| GSN | 89.2% | 94.5% | 74.9% | 87.5% | 79.8% | 87.9% | 85.2% |
| GSN_noL | 89.1% | 94.3% | 74.7% | 87.4% | 78.7% | 87.8% | 84.8% |
| GSN_w | 89.5% | 94.4% | 75.9% | 87.8% | 80.9% | 88.3% | 85.7% |
| GSN_w_mc | **90.2%** | **94.8%** | **76.9%** | **88.3%** | **82.3%** | **88.9%** | **86.5%** |

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| GSN_w | 89.5% | 94.4% | 75.9% | 87.8% | 80.9% | 88.3% | 85.7% |
| GSN_w_mc | **90.2%** | **94.8%** | **76.9%** | **88.3%** | **82.3%** | **88.9%** | **86.5%** |

| Method | Imp Surf | Building | Low_veg | Tree | Car | Overall Accuracy | Mean $F_1$ Score |
|---|---|---|---|---|---|---|---|
| FCN-8s [12] | 87.1% | 91.8% | **75.2%** | 86.1% | 63.8% | 85.9% | 80.8% |
| SegNet [14] | 82.7% | 89.1% | 66.3% | 83.9% | 55.7% | 82.1% | 75.5% |
| Deeplab-v2 [21] | 88.5% | 93.5% | 73.9% | 86.9% | **84.7%** | 86.9% | 83.5% |
| RefineNet [15] | 88.1% | 93.3% | 74.0% | 87.1% | 65.1% | 86.7% | 81.5% |
| GSN | **89.2%** | **94.5%** | 74.9% | **87.5%** | 79.8% | **87.9%** | **85.2%** |

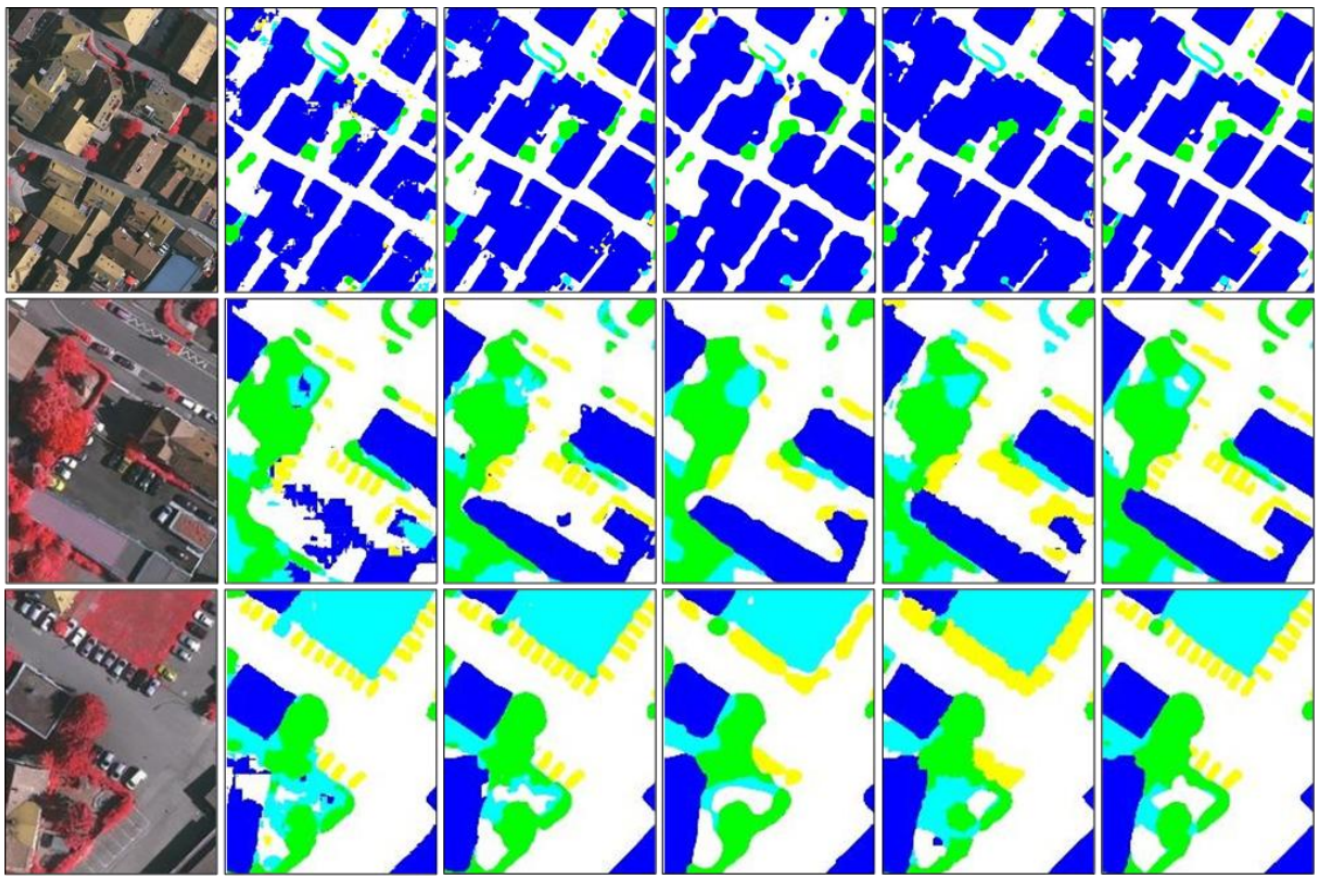
# Experimental evaluation


- Evalation of the ISPRS organizers

| Method | Imp Surf | Building | Low_veg | Tree | Car | Overall Accuracy | Mean $F_1$ Score |
|---|---|---|---|---|---|---|---|
| UPB [43] | 87.5% | 89.3% | 77.3% | 85.8% | 77.1% | 85.1% | 83.4% |
| ETH_C [44] | 87.2% | 92.0% | 77.5% | 87.1% | 54.5% | 85.9% | 79.7% |
| UOA [45] | 89.8% | 92.1% | 80.4% | 88.2% | 82.0% | 87.6% | 86.5% |
| ADL_3 [26] | 89.5% | 93.2% | 82.3% | 88.2% | 63.3% | 88.0% | 83.3% |
| RIT_2 [46] | 90.0% | 92.6% | 81.4% | 88.4% | 61.1% | 88.0% | 82.7% |
| DST_2 [8] | 90.5% | 93.7% | 83.4% | 89.2% | 72.6% | 89.1% | 85.9% |
| ONE_7 [47] | 91.0% | 94.5% | 84.4% | 89.9% | 77.8% | 89.8% | 87.5% |
| DLR_9 [28] | **92.4%** | **95.2%** | **83.9%** | **89.9%** | 81.2% | **90.3%** | 88.5% |
| GSN | 92.2% | 95.1% | 83.7% | **89.9%** | **82.4%** | **90.3%** | **88.7%** |

# Experimental evaluation

- Visual comparisons between GSN and other related methods on ISPRS test set



# Conclusions


- The ECM can effectively help for integrating contextual information from the upper layers and details from the lower layers
- The approach has the potential to perform better. Actually, the pixels in a certain region are interrelated. However, we calculate the entropy map (gate) pixel-to-pixel, which ignores the relationships between surrounding pixels.

# References I



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Wang, Hongzhen et al. “Gated Convolutional Neural Network for Semantic Segmentation in High-Resolution Images”. Em: *Remote Sensing* 9.5 (2017), p. 446.