

CN24 Open Source Deep Learning Framework

CNN Framework especially designed for scene understanding [1]

- Graph-based network structure can be freely specified
- **OpenCL**, MKL, ACML and dependency-free reference backends
- Hybrid patch-wise and fully convolutional design for fast prediction and efficient training
- 3-clause **BSD license** suitable for research and commercial applications



input image

cvjena.github.io/cn24/

Method Details

- Fully convolutional networks (FCN) [6] for prediction speed-up (up to 100x) over patch-wise approach
- Patch-wise training leads to faster optimization
- Real-time segmentation of VGA-sized inputs
- Incorporating position information as spatial priors
- Post-processing: quality enhancement of network outputs using unsupervised segmentation [5]
- Weighting: optimization with **inverse class frequency weights** accounts for imbalanced training set

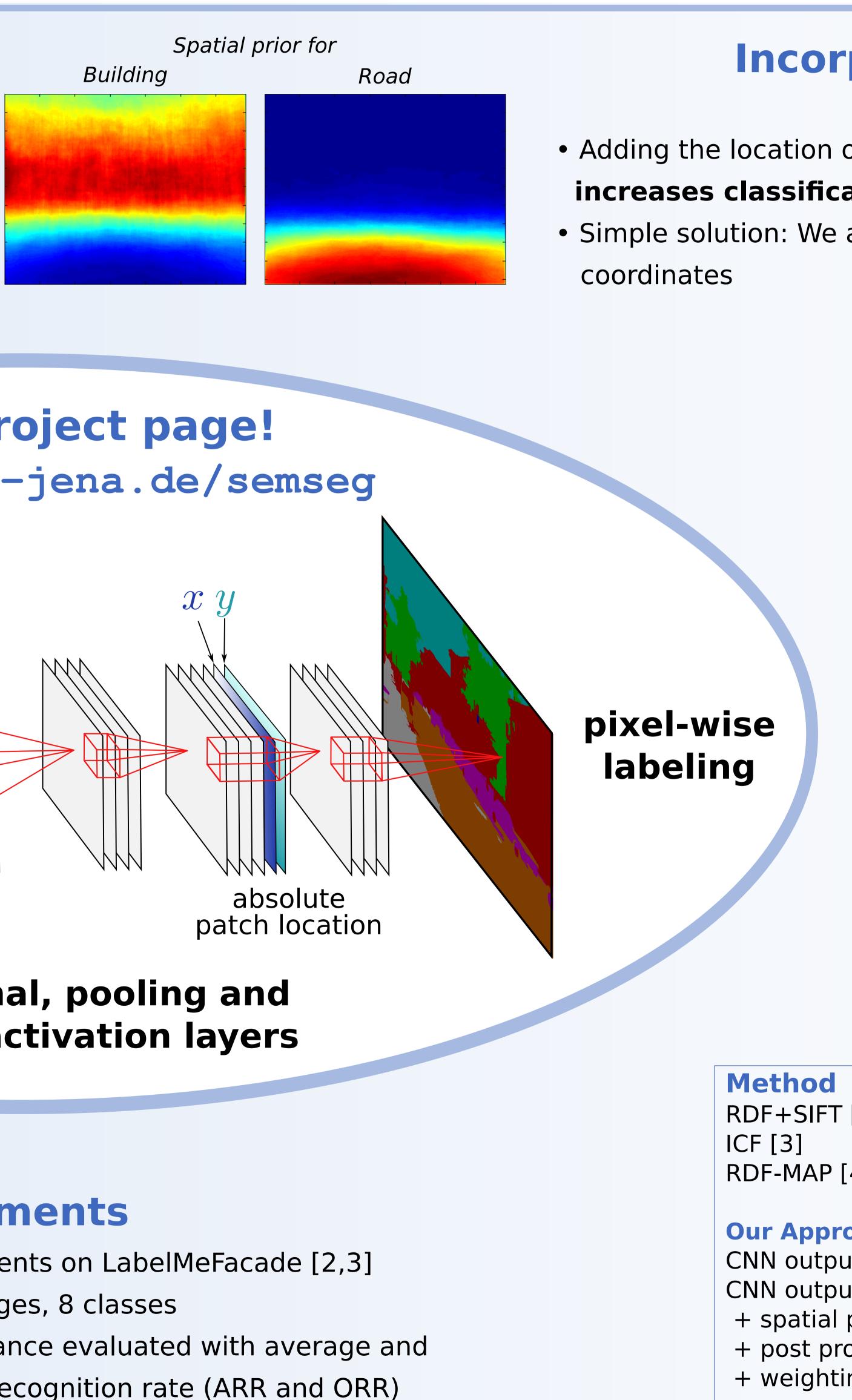
[1] Brust et al.: Convolutional Patch Networks with Spatial Prior for Road Detection and Urban Scene Understanding, In VISAPP, 2015, 510-517 [3] Fröhlich, Rodner, Denzler: Semantic Segmentation with Millions of Features: Integrating Multiple Cues in a Combined Random Forest Approach, In ACCV, 2012, 218-231
[5] Felzenszwalb, Huttonlocher: Efficient Graph-Based Image Segmentation, In IJCV 59(2), 2004, 167-181
[6] Long, Shelhamer, Darrell: Fully Convolutional Networks for Semantic Segmentation In CVPR, 2014, 548-555 [2] Fröhlich, Rodner, Denzler: A Fast Approach for Pixelwise Labeling of Facade Images, In ICPR, 2010, 3029-3032

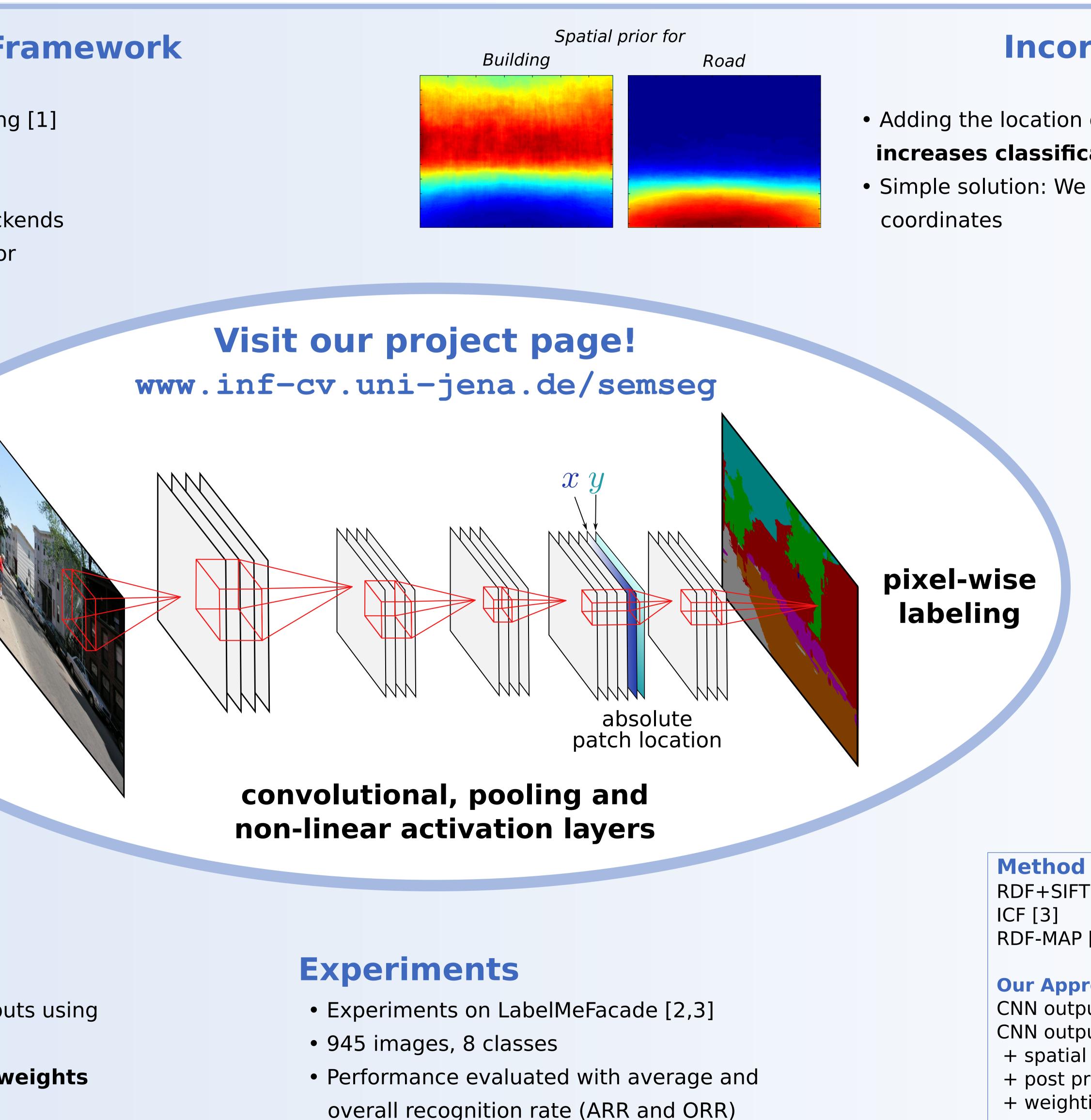
Efficient Convolutional Patch Networks for Scene Understanding

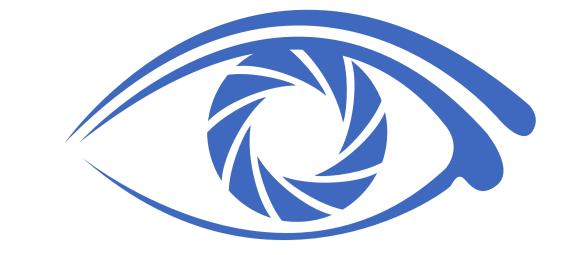
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Incorporating Spatial Priors

 Adding the location of a patch to the network's input increases classification performance significantly • Simple solution: We add additional input layers with pixel

Qualitative Results FFFF FFF pavement unlabeled

Quantitative Results

	ORR	ARR
[2]	49.06%	44.08%
	67.33%	56.61%
[4]	71.28%	-
oach		
uts (FCN training)	58.17%	29.48%
uts (patch-wise training)	67.87%	42.89%
prior	72.21%	47.74%
rocessing	74.33%	47.77%
ing	63.41%	58.98 %