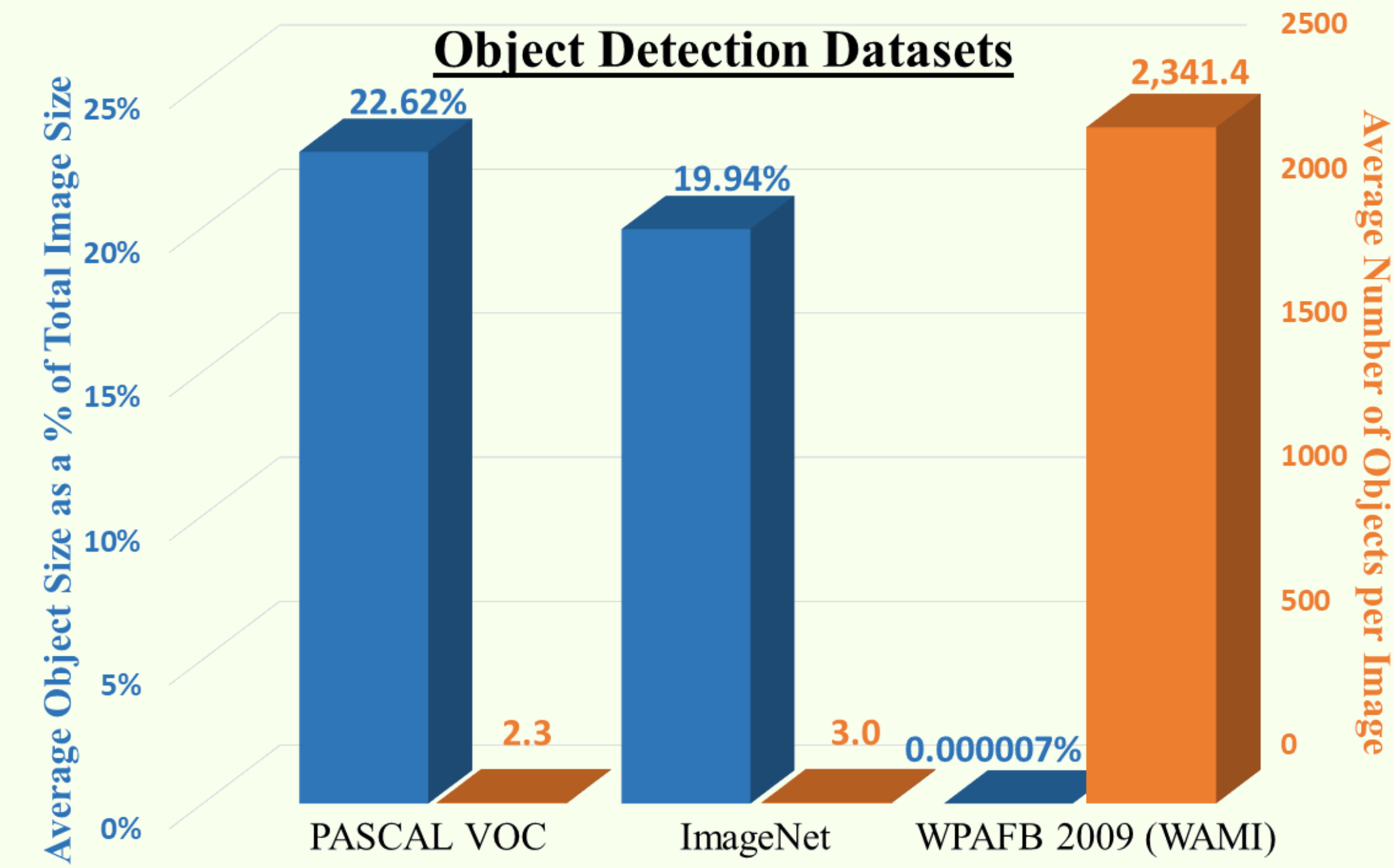


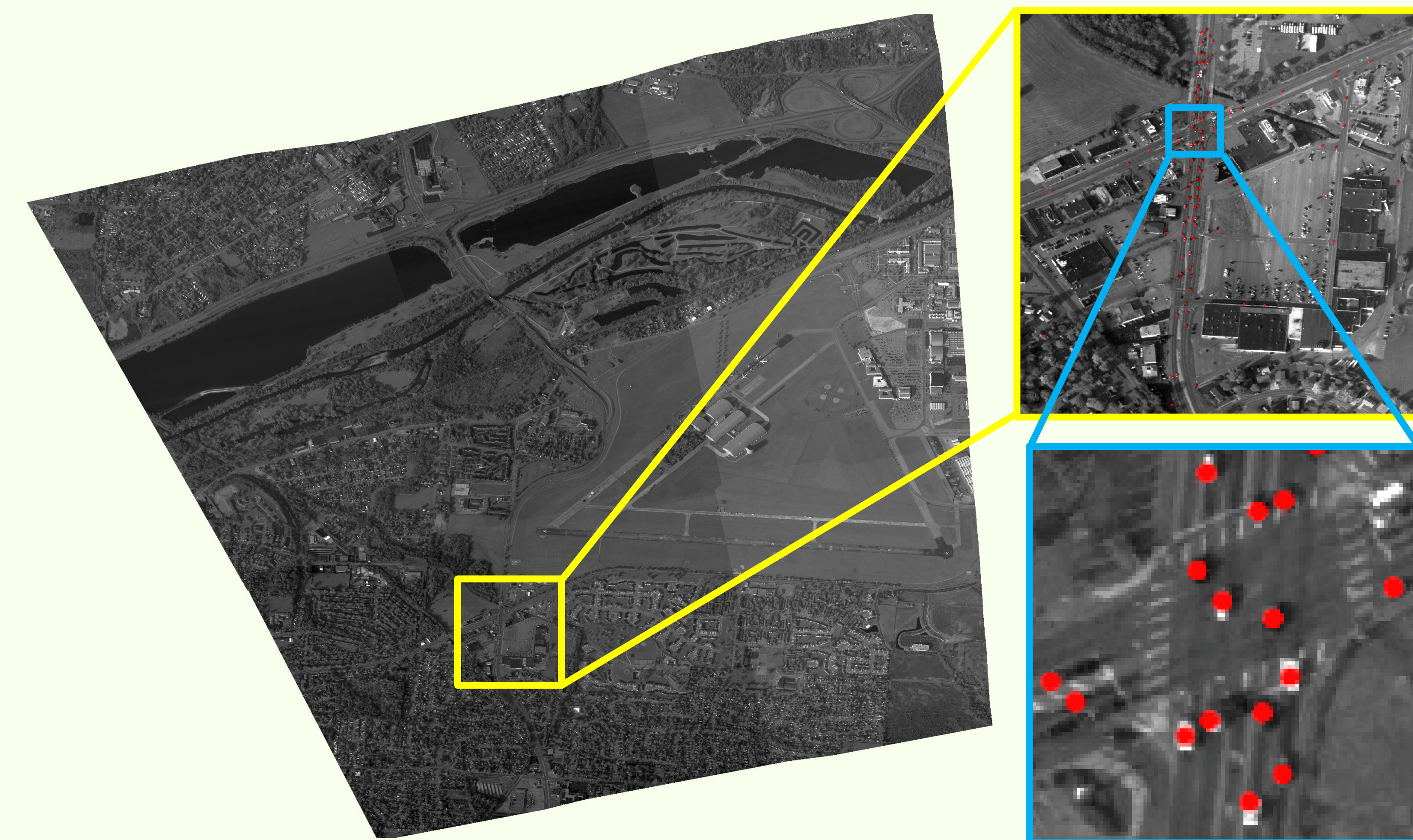
Problem: Object Detection in Wide Area Motion Imagery



- WAMI video frames contain thousands of objects compared to 2-3 in "standard" object detection.
- WAMI objects are extremely small in relation to the search space.

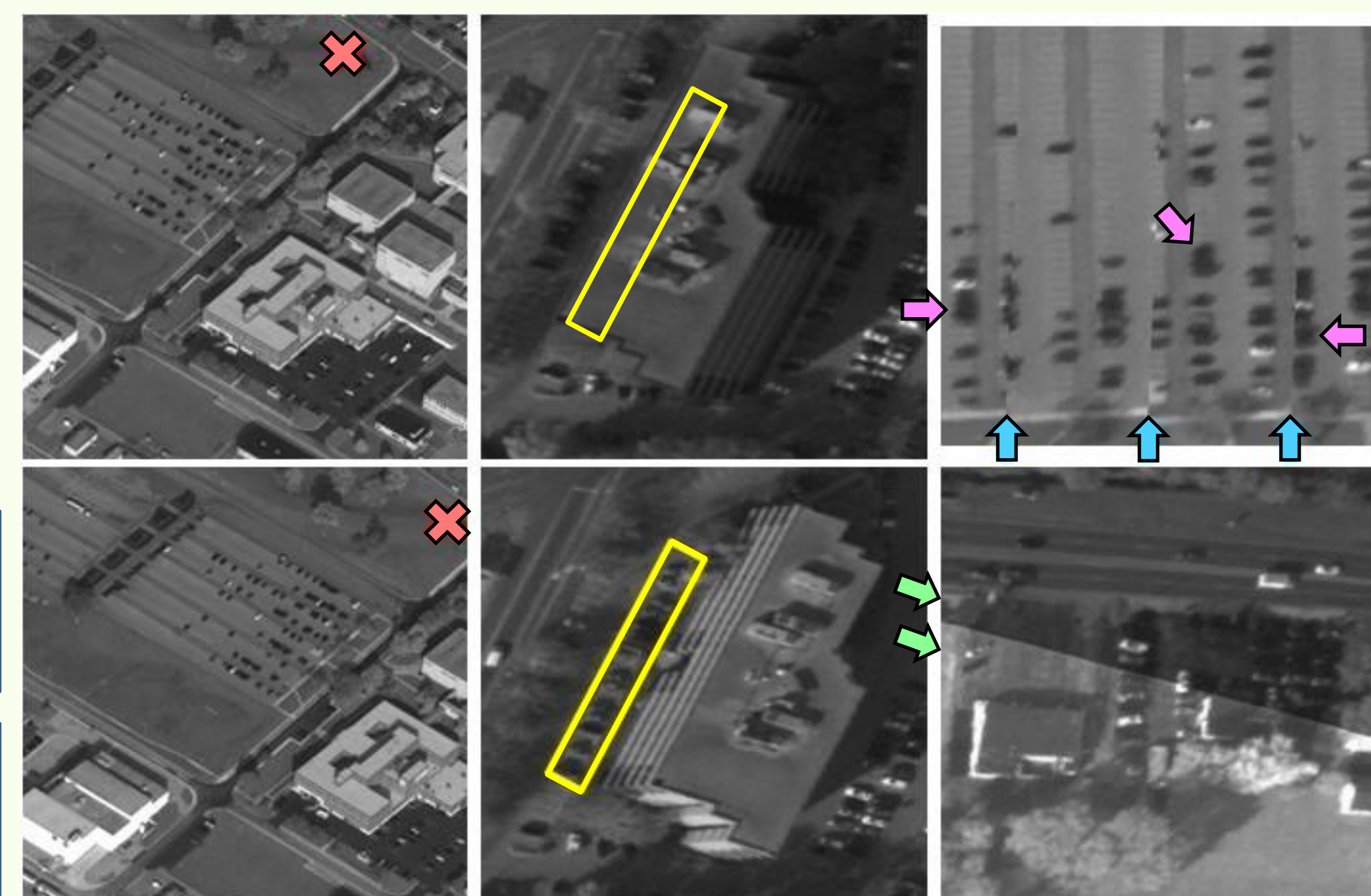
WPAFB 2009 Dataset

- 6 slightly-overlapping cameras; 19 sq. km.; 1.25 fps; Grayscale;
- ~315 MP per frame; Vehicle size: ~9x18 pixels; Pixel size ~1/4 m²
- ~2.4 million annotations across 1,025 frames of video.



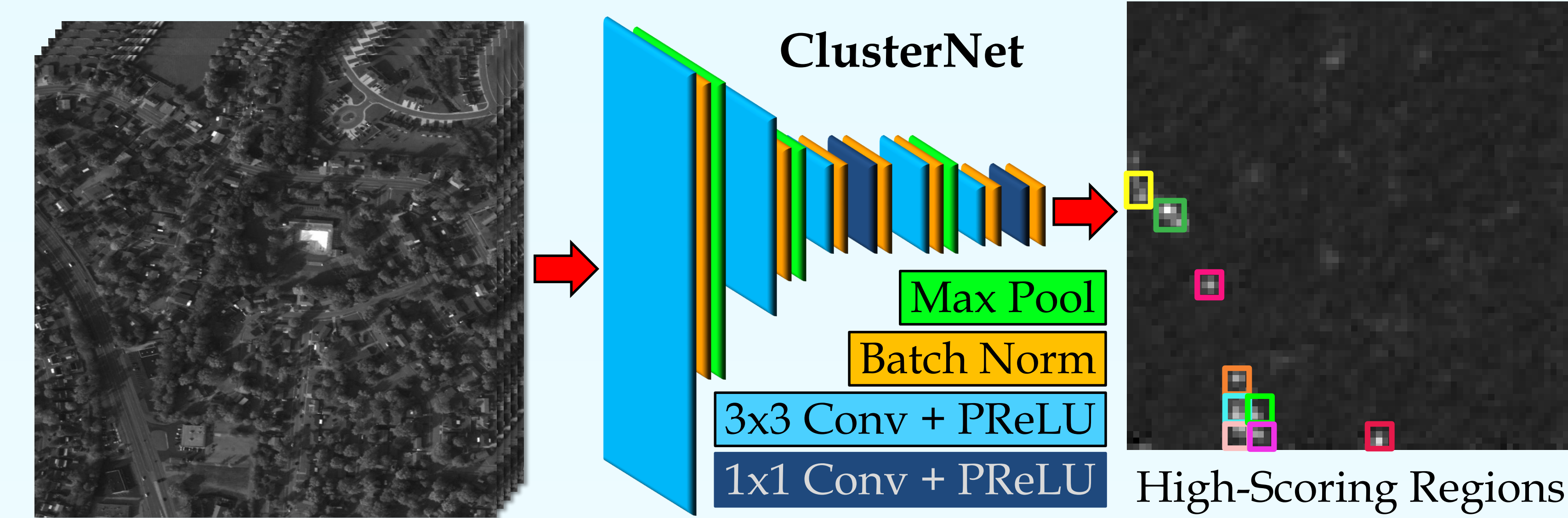
Challenges

- Low frame rate
- Motion parallax
- Mosaic Seams
- Blurred/Unclear Object Boundaries
- Inconsistent Illumination

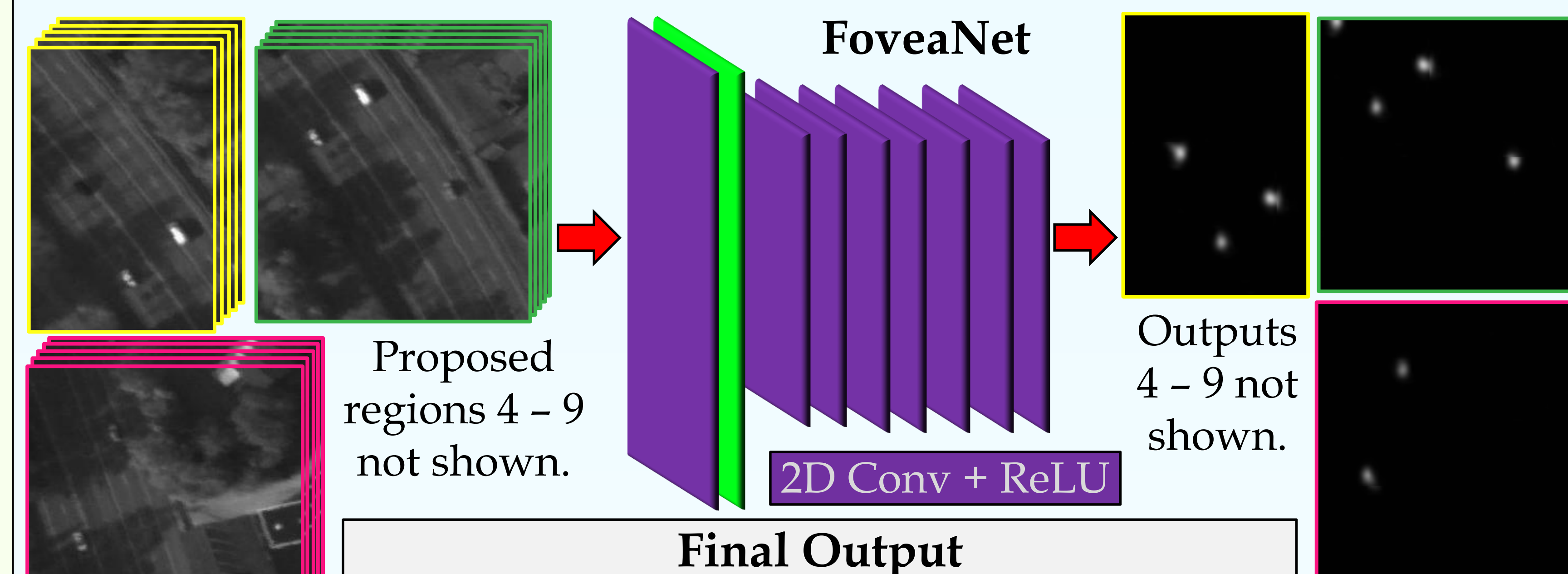


Proposed Method: ClusterNet & FoveaNet Two-Stage Fully Convolutional Neural Network

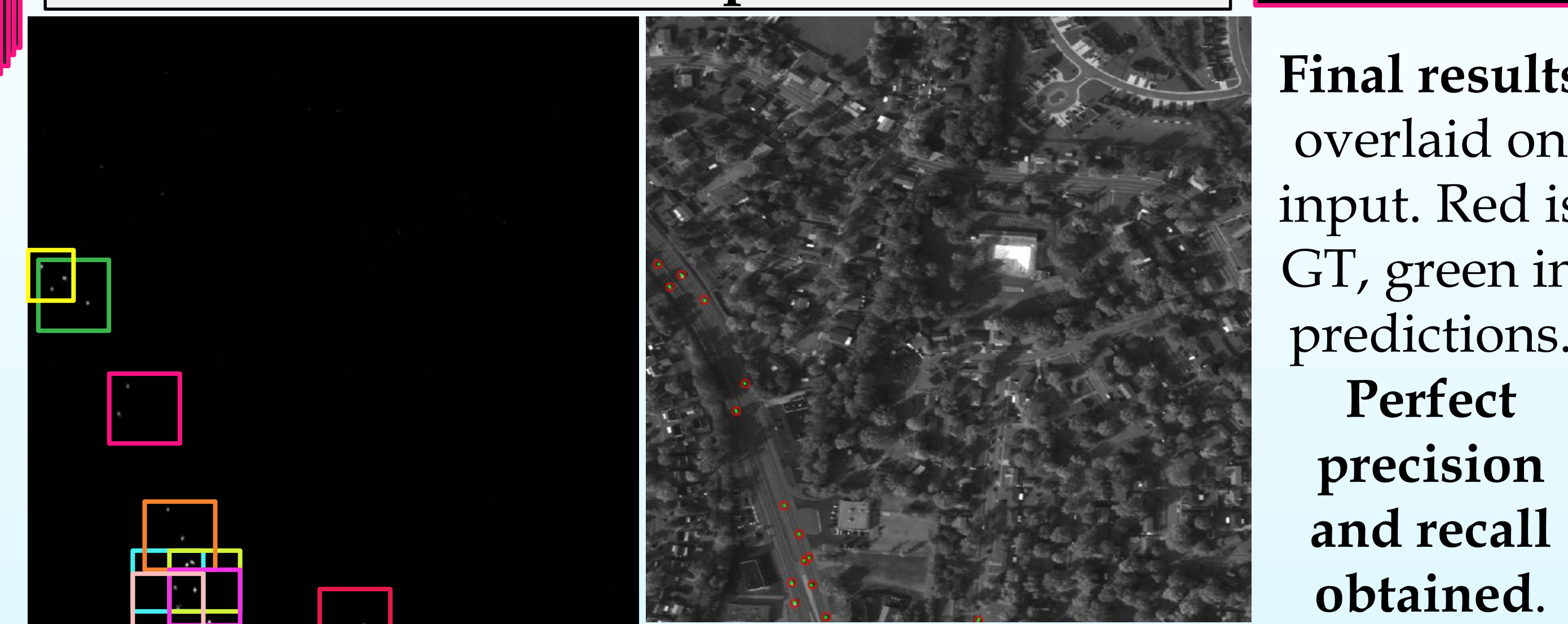
- First Stage: ClusterNet detects Regions of Objects of Interest.
- ClusterNet effectively reduces the search space to regions containing one to several hundred vehicles per output neuron.
- Second Stage: FoveaNet extracts the effective receptive field of high-scoring output neurons for fine-grained localization.



Regions proposed by ClusterNet: 9 out of 324 possible

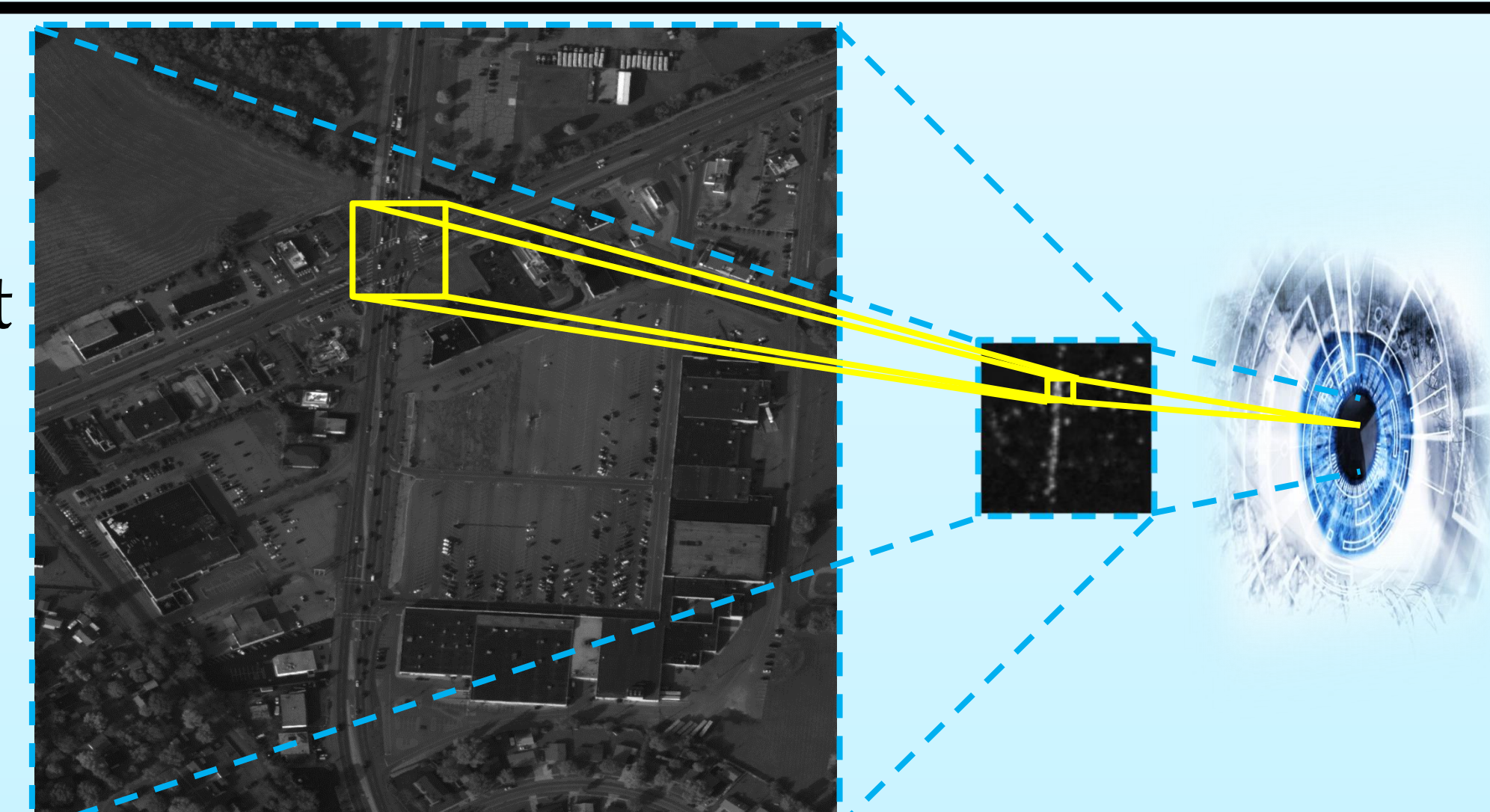


Reassembled outputs of FoveaNet. Non-Boxed regions filled with 0s.

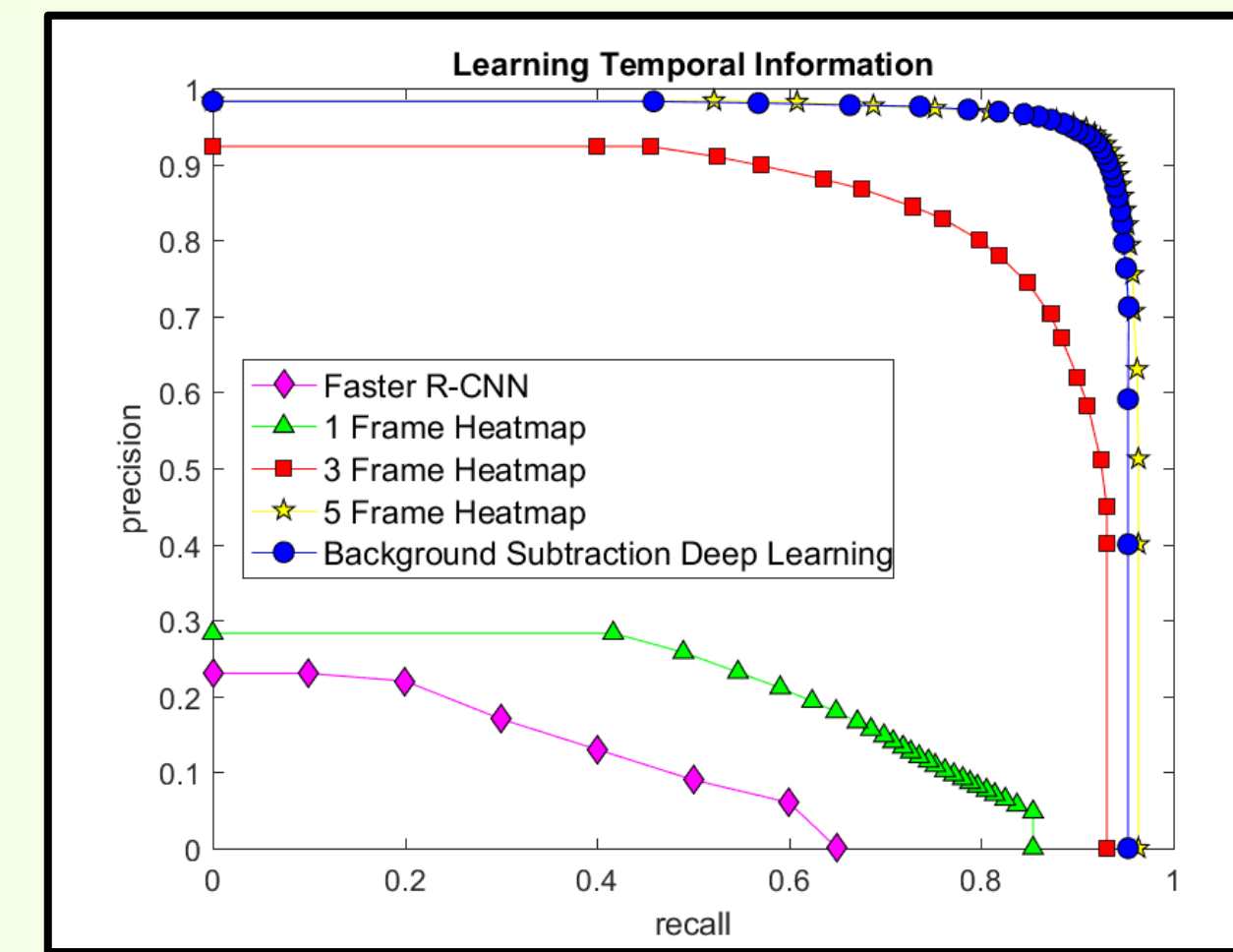


Final results overlaid on input. Red is GT, green in predictions. Perfect precision and recall obtained.

SUMMARY: ClusterNet effectively reduces the search space while FoveaNet scans the receptive field of high scoring neurons in ClusterNet's output to produce fine-grained localization of vehicles.



Qualitative Results: Moving Object Detection Results

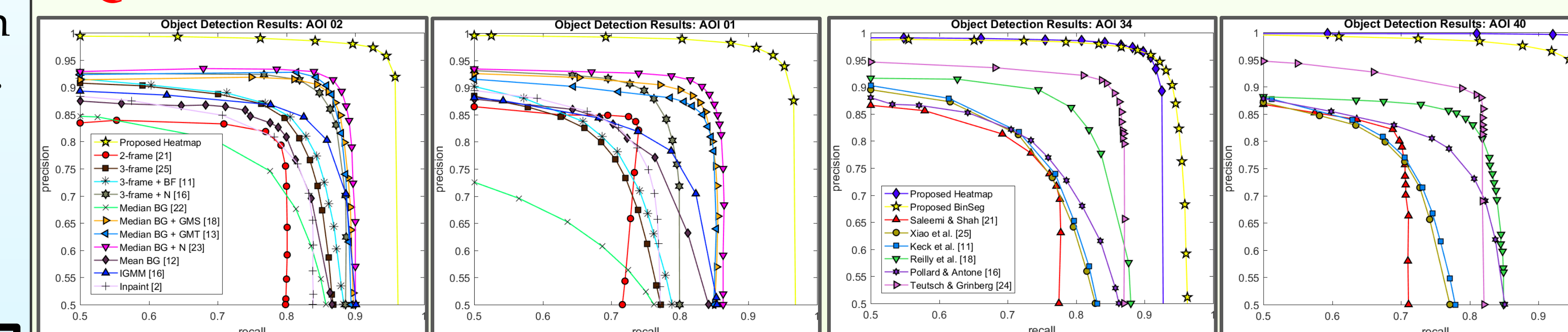


^ Explicit temporal relationship computed (background subtraction) vs. varying amounts of temporal information implicitly modeled by CNN vs. Faster R-CNN.

Stationary Object Detection Results



Quantitative Results:



Comparison of F₁ Scores on Eight Crop and Aligned Sections of the WPAFB 2009 Dataset

Method	01	02	03	04	34	40	41	42
Sommer <i>et al.</i> [27]	0.866	0.890	0.900	0.804	x	x	x	x
Shi [25]	0.645	0.760	0.861	0.575	x	x	x	x
Liang <i>et al.</i> [12]	0.842	0.880	0.903	0.760	x	x	x	x
Kent <i>et al.</i> [10]	0.767	0.807	0.668	0.711	x	x	x	x
Aeschliman <i>et al.</i> [2]	0.764	0.795	0.875	0.679	x	x	x	x
Pollard & Antone (3-frame + N) [16]	0.816	0.868	0.892	0.805	x	x	x	x
Saleemi & Shah [24]	0.783	0.793	0.876	0.733	0.755	0.749	0.762	x
Xiao <i>et al.</i> [29]	0.738	0.820	0.868	0.687	0.761	0.733	0.700	x
Keck <i>et al.</i> [9]	0.743	0.825	0.876	0.695	0.763	0.737	0.708	x
Reilly <i>et al.</i> [19]	0.850	0.876	0.889	0.783	0.826	0.817	0.799	x
Pollard & Antone (IGMM) [16]	0.785	0.835	0.776	0.716	0.766	0.778	0.616	x
Teutsch & Grinberg [28]	x	x	x	x	0.874	0.847	0.854	x
Prokaj & Medioni [17]	x	x	x	x	x	x	x	0.631
Proposed Method	0.947	0.951	0.942	0.887	0.933	0.983	0.928	0.927

Project Pages

<http://crvc.ucf.edu/projects/FullyConvolutionalDNN/>
<https://bit.ly/2sTvhju>

