

# Efficient Facade Segmentation using Auto-Context

## Supplementary Material

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We present more qualitative (Figures 1 to 6) and quantitative (Table 1 and Table 2) facade segmentation results. The images have been selected based on the absolute overall pixel-accuracy of ST3 and include images with the (i) highest, (ii) average, and (iii) lowest performance.

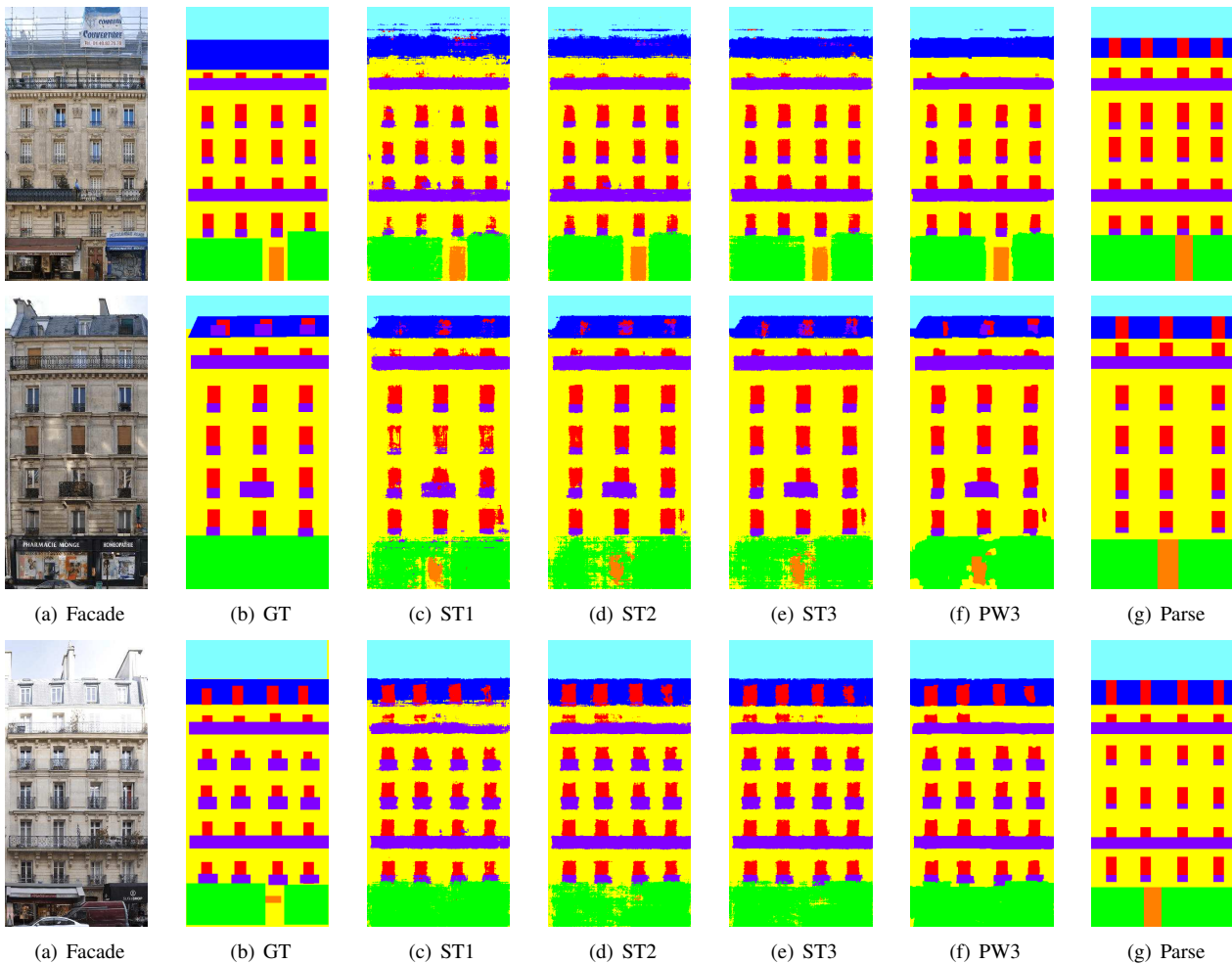


Figure 1. (a) Sample facade images from ECP dataset, (b) ground truth segmentation, (c,d,e) result of various classification stages (ST1, ST2, ST3) of the auto-context method, (f) Potts model using ST3 as unaries, and (g) the result obtained by applying reinforcement learning [8] using the output of ST3.

\*The first two authors contribute equally to this work.

(a) CMP Dataset

Class	[6]	Auto Context			AC + Potts Model		
		ST1	ST2	ST3	PW1	PW2	PW3
Background	58	67.1	71.8	<b>72.6</b>	68.0	<b>72.6</b>	73.1
Facade	73	74.6	75.3	75.2	<b>80.5</b>	79.9	79.3
Window	61	71.6	76.1	77.0	74.1	77.4	<b>78.1</b>
Door	<b>54</b>	37.9	45.5	47.0	39.6	46.4	48.7
Cornice	41	39.1	47.5	<b>49.6</b>	40.0	48.3	<b>50.1</b>
Sill	27	21.1	32.8	<b>36.2</b>	16.9	30.3	34.6
Balcony	46	31.6	44.1	46.7	31.6	45.2	<b>48.1</b>
Blind	<b>48</b>	22.7	35.8	40.1	19.5	34.7	39.9
Deco	<b>24</b>	10.4	13	13.8	6.1	10.0	11.4
Molding	54	63.2	65.4	66.5	64.2	66.0	<b>67.2</b>
Pillar	<b>25</b>	5.71	11.2	13.6	1.33	7.72	9.78
Shop	<b>59</b>	40.9	45.6	45.6	42.8	46.7	46.8
<b>Average</b>	47.5	40.50	47.00	<b>48.65</b>	40.38	47.1	<b>48.92</b>
<b>Overall</b>	60.3	61.83	65.47	66.24	64.46	67.48	<b>68.08</b>
<b>IoU</b>	-	29.26	34.46	35.86	30.67	36.02	<b>37.47</b>

(b) Graz Dataset

Class	Auto Context (AC)			AC + Potts Model			[7]
	ST1	ST2	ST3	PW1	PW2	PW3	
Door	57.3	62.4	<b>62.7</b>	57.3	<b>62.8</b>	<b>63</b>	41
Window	78.2	81.2	<b>81.5</b>	77.8	80.6	80.9	60
Wall	94.9	94.7	94.9	<b>95.8</b>	<b>95.6</b>	<b>95.8</b>	84
Sky	87.4	<b>91.2</b>	<b>90.5</b>	87.7	<b>91.4</b>	<b>90.6</b>	<b>91</b>
<b>Average</b>	79.47	82.40	82.42	79.65	<b>82.61</b>	<b>82.56</b>	69
<b>Overall</b>	90.18	91.02	91.16	90.78	<b>91.53</b>	<b>91.68</b>	78
<b>IoU</b>	71.25	73.31	73.25	72.49	<b>74.45</b>	<b>74.39</b>	58

(c) labelMeFacades Dataset

Class	[2]	[5]	Auto Context(AC)			AC + Potts Model		
			ST1	ST2	ST3	PW1	PW2	PW3
Building	-	-	87.7	88.1	88.2	<b>92.7</b>	91.8	92.1
Car	-	-	47.1	53.6	54.8	51.1	57.0	<b>58.2</b>
Door	-	-	<b>6.52</b>	6.03	5.12	2.61	3.22	1.71
Pavement	-	-	24	<b>25.3</b>	<b>24.6</b>	22.0	24.2	23.3
Road	-	-	80.3	82.1	84.5	85.3	85.1	<b>87.6</b>
Sky	-	-	86.2	87.2	87.4	88.3	<b>88.6</b>	<b>88.9</b>
Vegetation	-	-	53.3	<b>57.5</b>	<b>57.6</b>	53.4	<b>58.1</b>	<b>57.9</b>
Window	-	-	20.3	22.6	<b>25.4</b>	13.0	16.9	19.5
Various	-	-	19.9	<b>20.6</b>	<b>21.0</b>	11.6	12.2	12.1
<b>Average</b>	<b>56.61</b>	-	47.26	49.22	49.84	46.68	48.56	49.04
<b>Overall</b>	67.33	71.28	71.52	72.9	73.46	74.1	74.62	<b>75.23</b>
<b>IoU</b>	-	35.96	37.01	38.69	39.36	37.74	38.96	<b>39.57</b>

Table 1. Segmentation results of various methods on CMP, Graz and labelMeFacades datasets. ST1, ST2, and ST3 correspond to the classification stages in the auto-context method. PW1, PW2, and PW3 refer to a Potts model using ST1, ST2, and ST3, respectively, as unaries. Published results are shown for comparisons. The method of [7] parses the image into a lattice representation and is not trying to maximize pixel accuracy results.

(a) eTRIMS Dataset

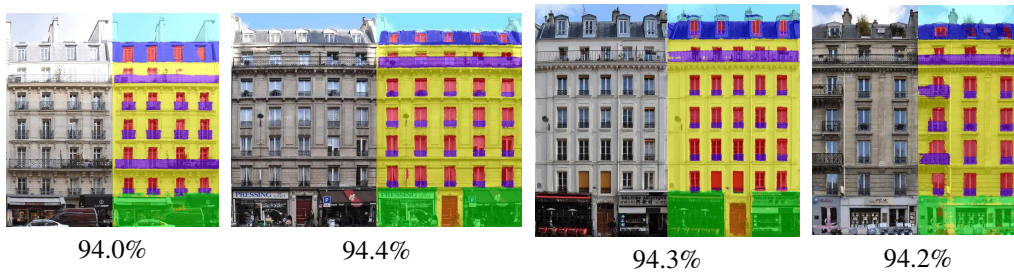
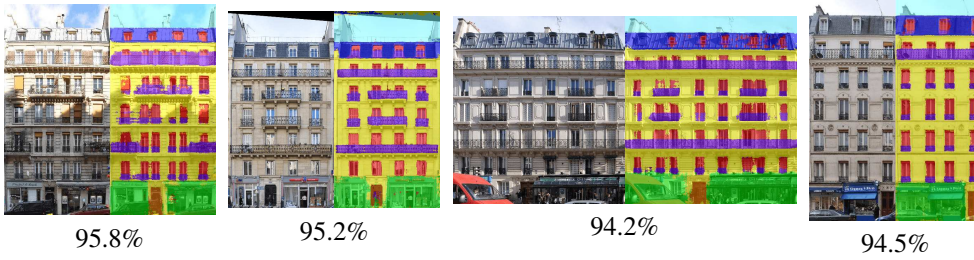
Class				Auto Context (AC)			AC + Potts Model		
	[4]	[1]	[3]	ST1	ST2	ST3	PW1	PW2	PW3
Building	91	91	84	90.3	90.5	90.9	<b>92.7</b>	<b>92.5</b>	<b>92.5</b>
Car	69	70	51	63.3	74.8	72.4	69.4	<b>79.1</b>	76.6
Door	18	18	<b>73</b>	62.7	62.3	63.6	66.0	63.6	65.3
Pavement	33	33	55	43.0	46.5	47.1	43.1	<b>48.6</b>	<b>48.8</b>
Road	55	57	81	78.2	82.3	80.3	80.9	<b>84.7</b>	82.1
Sky	93	97	<b>99</b>	97.6	<b>98.5</b>	<b>98.6</b>	98.2	<b>98.8</b>	<b>98.9</b>
Vegetation	89	90	92	91.1	92.1	92.3	92.4	<b>92.8</b>	<b>92.9</b>
Window	<b>74</b>	71	78	65.9	67.1	68.4	65.6	66.5	68.2
<b>Average</b>	65.3	65.9	66.4	74.01	76.78	76.7	76.04	<b>78.32</b>	78.14
<b>Overall</b>	83.16	83.84	83.40	84.68	85.95	86.12	86.39	<b>87.29</b>	<b>87.29</b>
<b>IoU</b>	-	-	-	58.7	61.26	61.48	61.49	63.39	<b>63.54</b>

Table 2. Segmentation results of various methods on eTRIMS dataset. ST1, ST2, and ST3 correspond to the classification stages in the auto-context method. PW1, PW2, and PW3 refer to a Potts model using ST1, ST2, and ST3, respectively, as unaries. Published results are shown for comparisons.

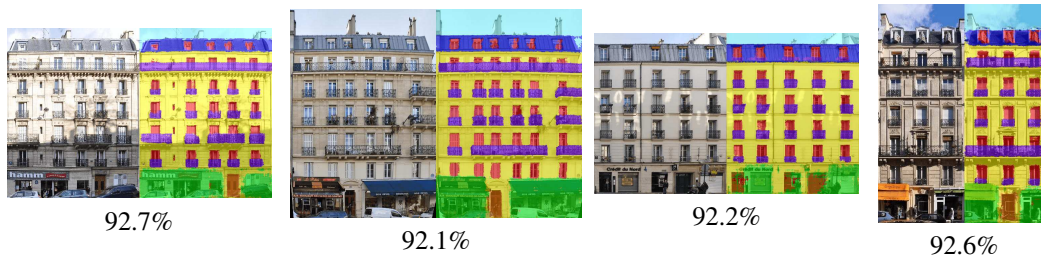
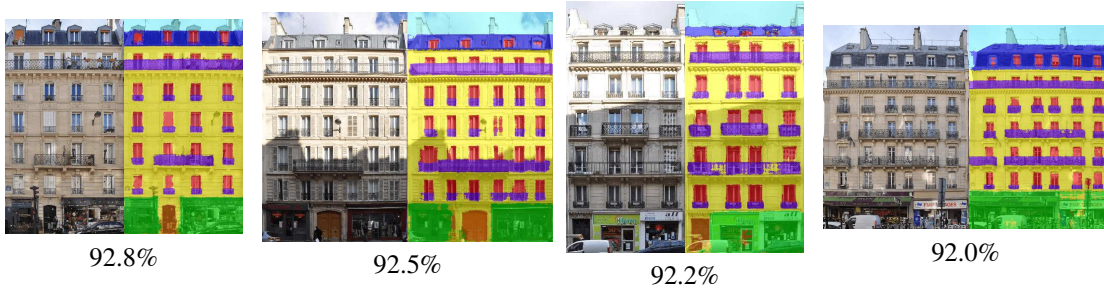
## References

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### Highest Performance



### Average Performance



### Lowest Performance

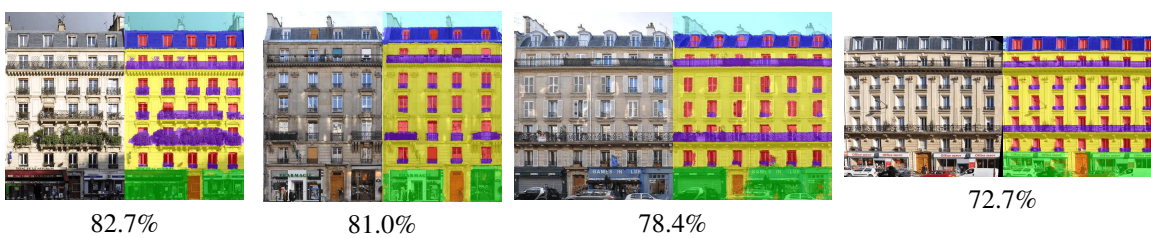
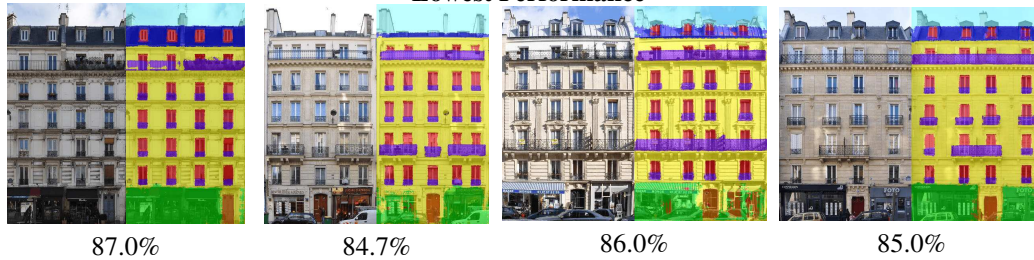
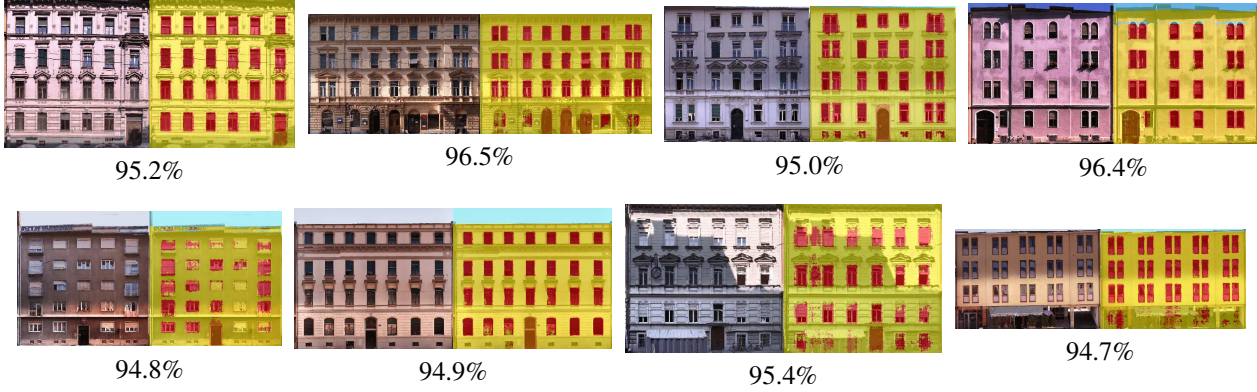


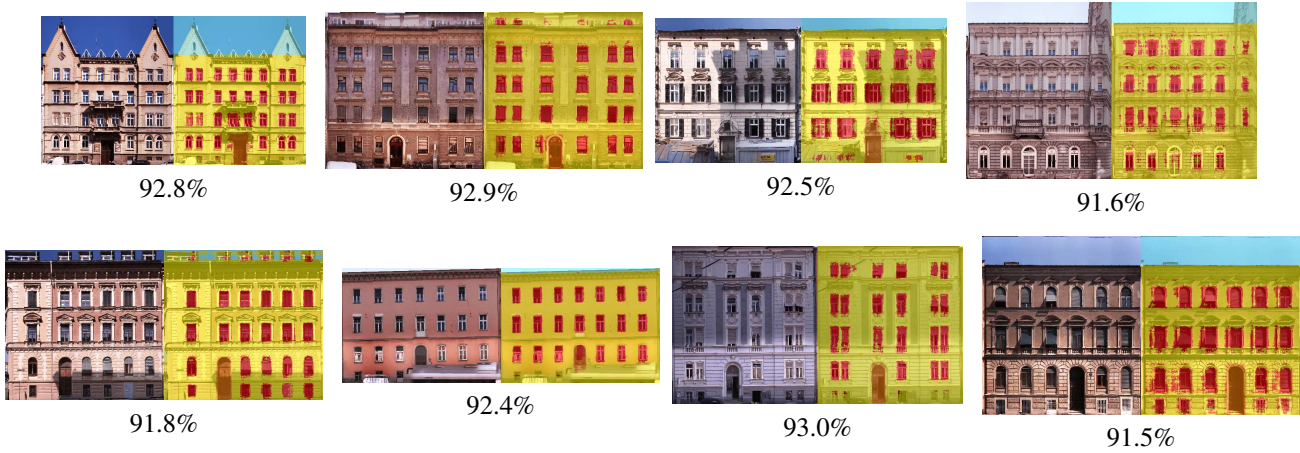
Figure 2. Qualitative results on ECP dataset images along with overall pixel accuracy (Stage-3 results).



### Highest Performance



### Average Performance

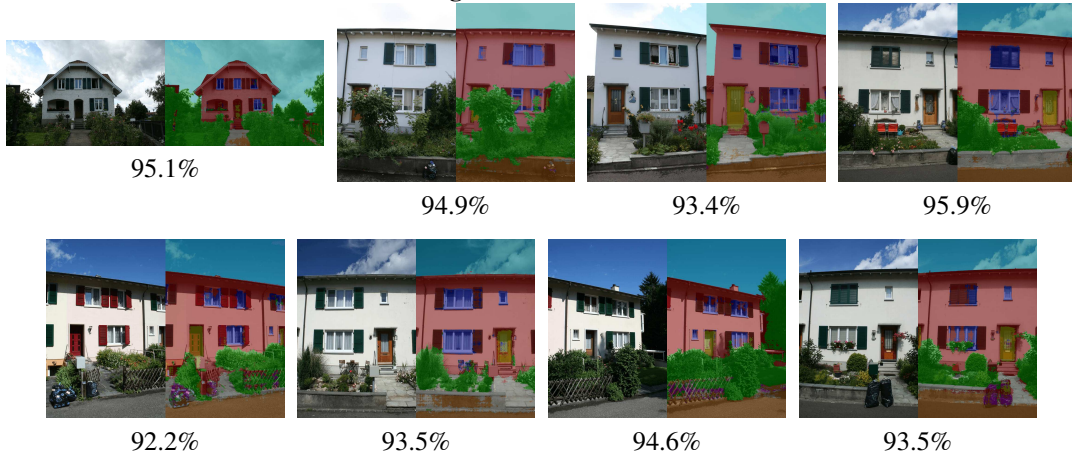


### Lowest Performance



Figure 3. Qualitative results on Graz dataset images along with overall pixel accuracy (Stage-3 Results).

### Highest Performance



### Average Performance



### Lowest Performance



Figure 4. Qualitative results on eTRIMS dataset images along with overall pixel accuracy (Stage-3 results).



### Highest Performance



### Average Performance

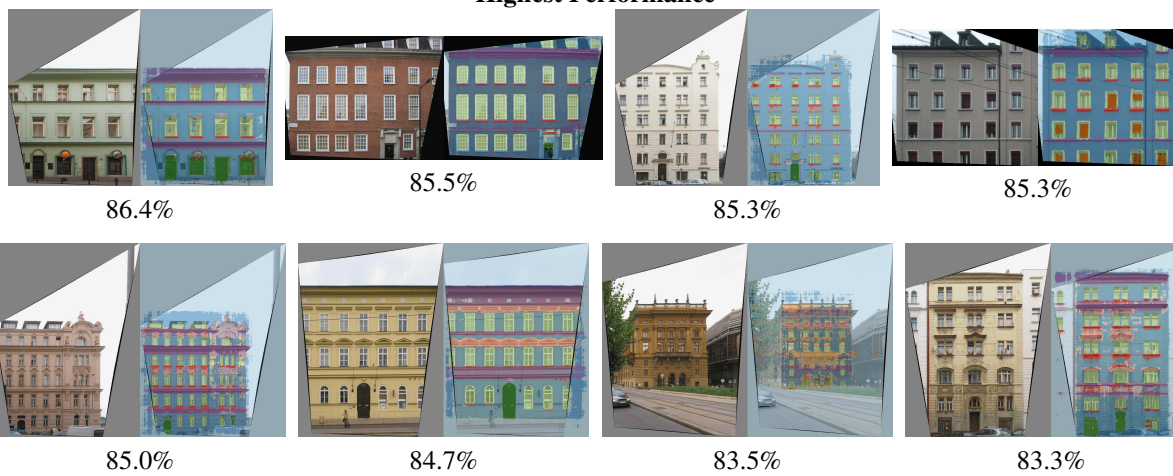


### Lowest Performance

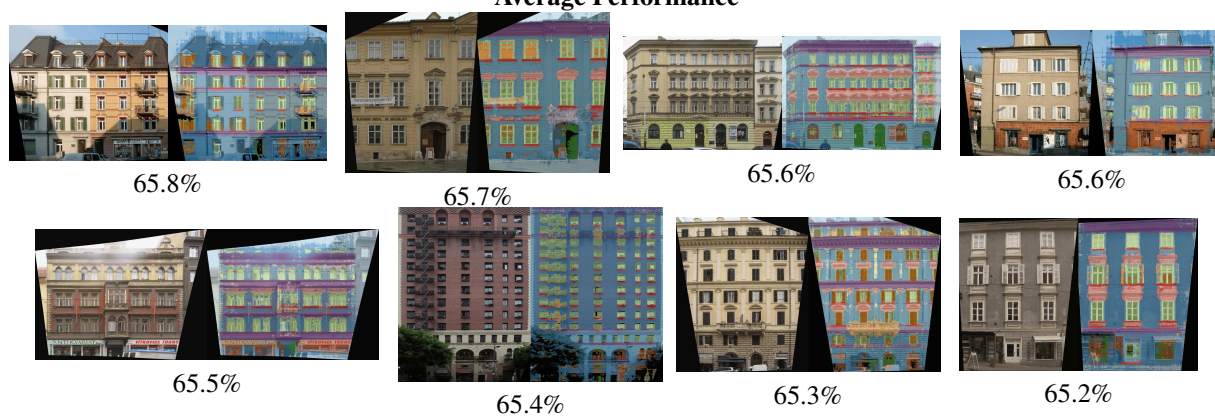


Figure 5. Qualitative results on labelmeFacades dataset images along with overall pixel accuracy (Stage-3 results).

### Highest Performance



### Average Performance



### Lowest Performance

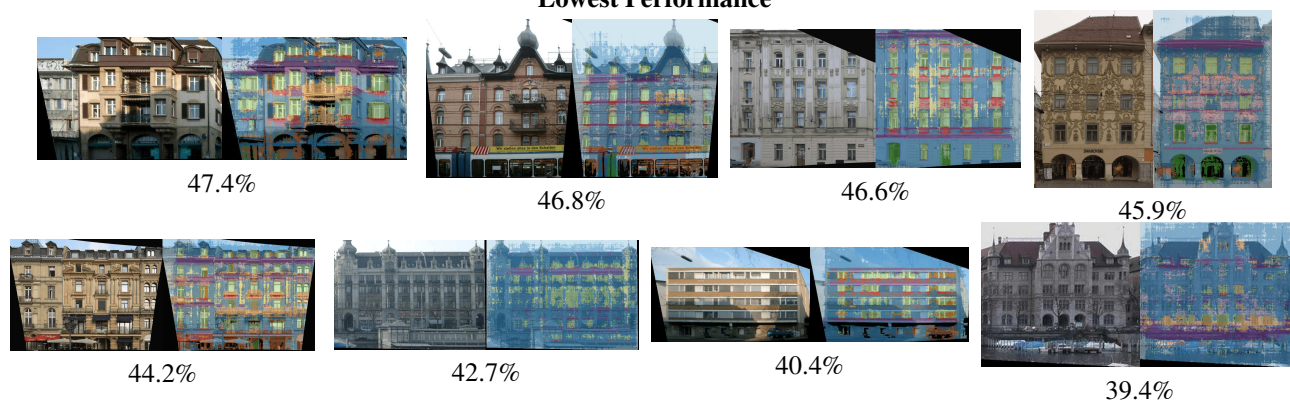


Figure 6. Qualitative results on CMP dataset images along with overall pixel accuracy (Stage-3 results).