Hyperrealistic Image Inpainting with Hypergraphs
Supplementary Material

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1. Additional Results

Here, we give some additional results from our network. We give the additional results on all four publicly available datasets, including CelebA-HQ [3], Places2 [2], Paris Street View [1] and Facades Dataset [4]. The results are provided for both center and irregular mask for all the datasets.

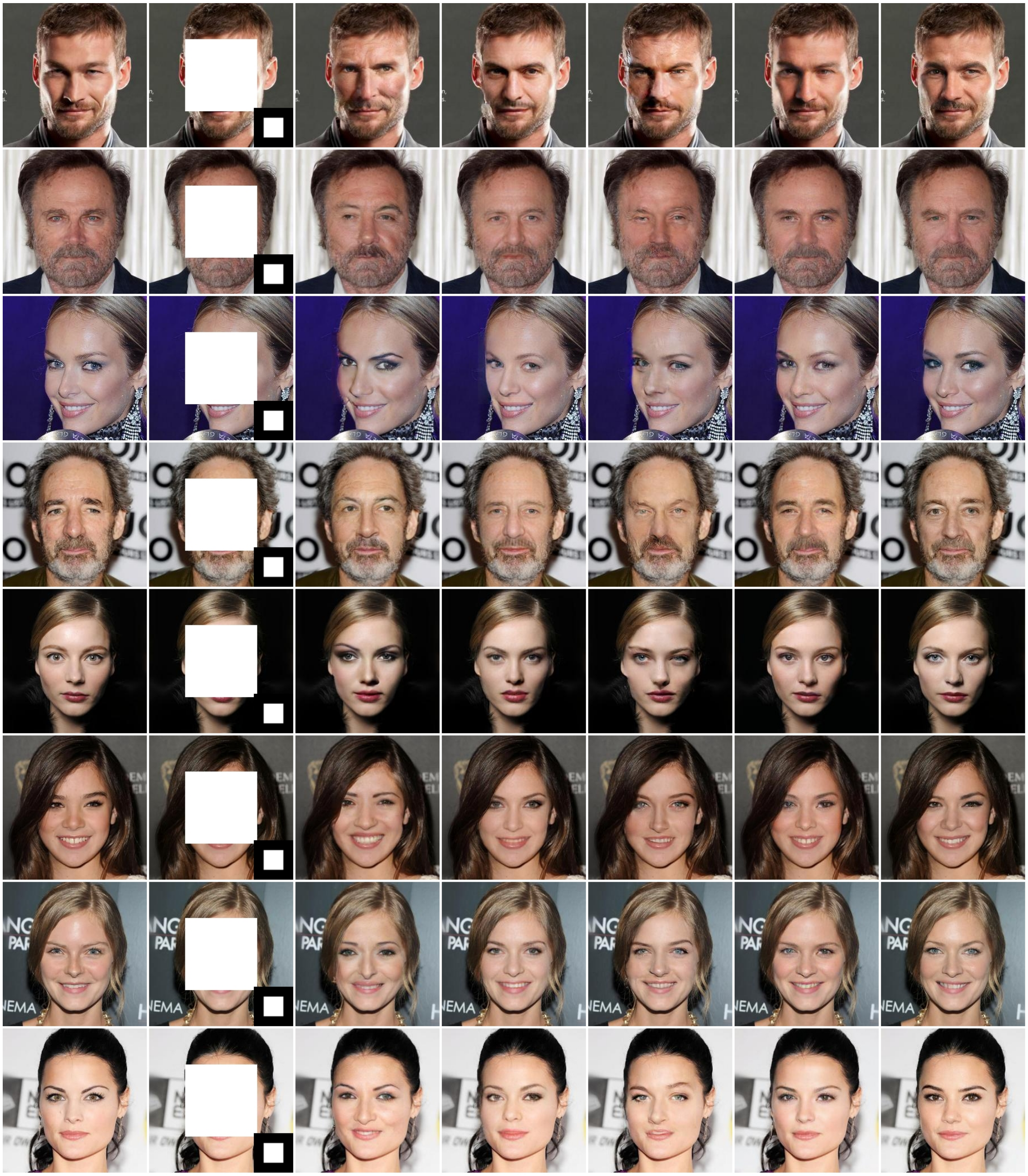
CelebA-HQ [3]: In Figure-1, we compare our method with the following state-of-the-art methods for center mask: a) pluralistic image completion (PICNet) [8], b) generative multi-column (GMCNN) [5], c) DeeFill-v2 [7], and d) Shift-Net (SN) [6]. Next, in Figure-2 and Figure-3 we compare our results for irregular mask..

Places2 [2]: In Figure-4, we evaluate our results on Places2 dataset for center mask. In Figure-5 and Figure-6 we compare our results with the state-of-the-art methods on random mask. We compare with a) pluralistic image completion (PICNet) [8], b) generative multi-column (GMCNN) [5], c) DeeFill-v2 [7], and d) Shift-Net (SN).

Paris Street View [1]: In Figure-7, we evaluate our results on Paris Street View dataset for center mask, and in Figure-8 we evaluate our results for irregular mask. The hole percentage in irregular mask is 40-60%.

Facades [4]: In Figure-9, we evaluate our results on Facades datasets with center mask, and in figure-10 we evaluate our results on irregular mask. Please note that we fine tune the model trained on Paris Street View datasets for evaluating on Facades Datasets.

We resize all the images to the scale of 256×256 for both training and evaluation purposes. The results are presented from the next page.



(a) Ground Truth (b) Input Image (c) PICNet (d) GMCNN (e) DeepFillV2 (f) SN (g) Ours

Figure 1. Qualitative Results on CelebA-HQ dataset with center mask. From left to right $a)$ Ground Truth, $b)$ Input Image, $c)$ Pluralistic (PICNet) [8], $d)$ GMCNN [5], $e)$ DeepFill-V2 [7], $f)$ Shift-Net (SN) [6], $g)$ Ours. All image are scaled to 256×256.

(a) Ground Truth (b) Input Image (c) PICNet (d) GMCNN (e) DeepFillV2 (f) SN (g) Ours

Figure 2. Qualitative Results on CelebA-HQ dataset with random mask. From left to right $a)$ Ground Truth, $b)$ Input Image, $c)$ Pluralistic (PICNet) [8], $d)$ GMCNN [5], $e)$ DeepFill-V2 [7], $f)$ Shift-Net (SN) [6], $g)$ Ours. All image are scaled to 256×256.

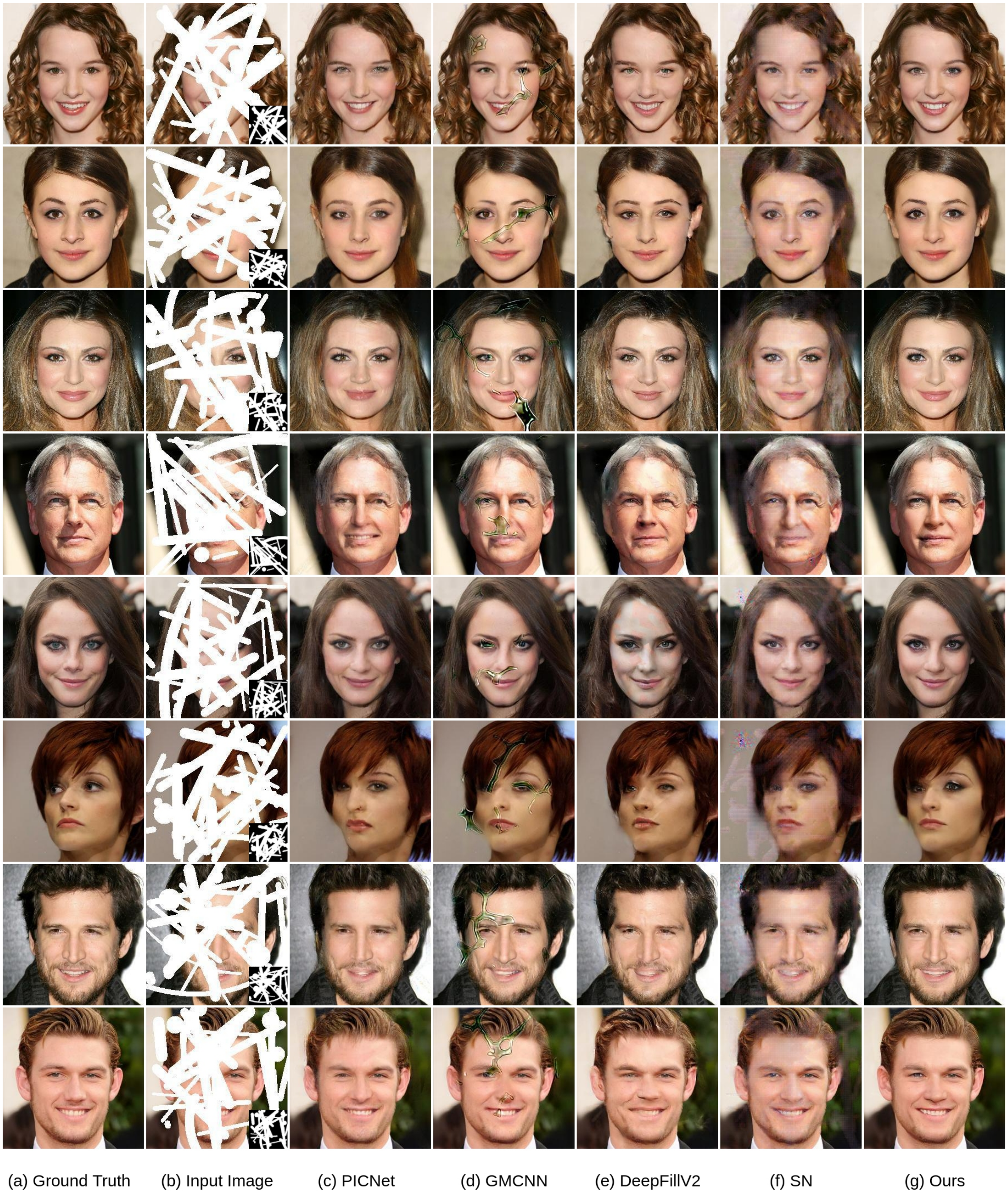
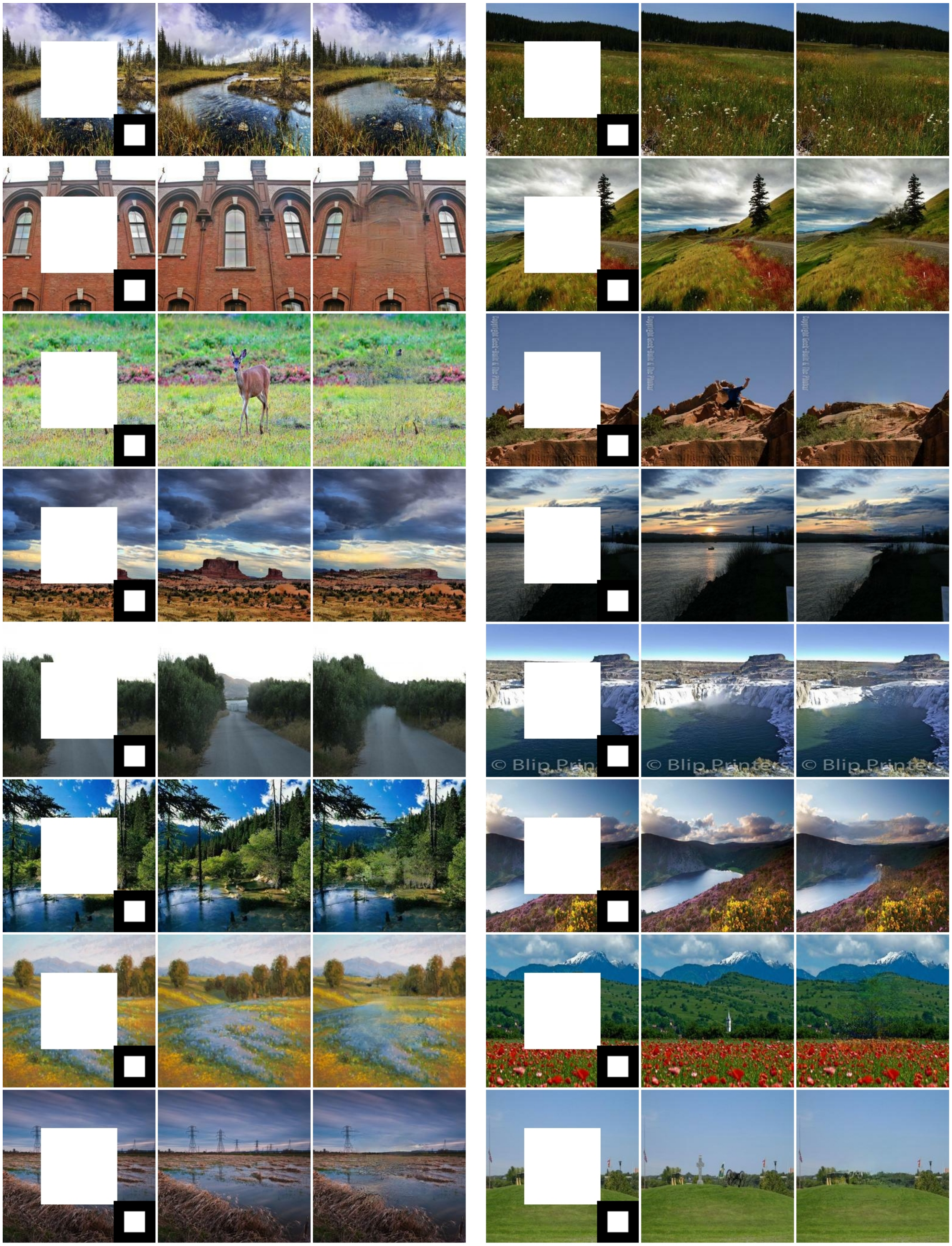
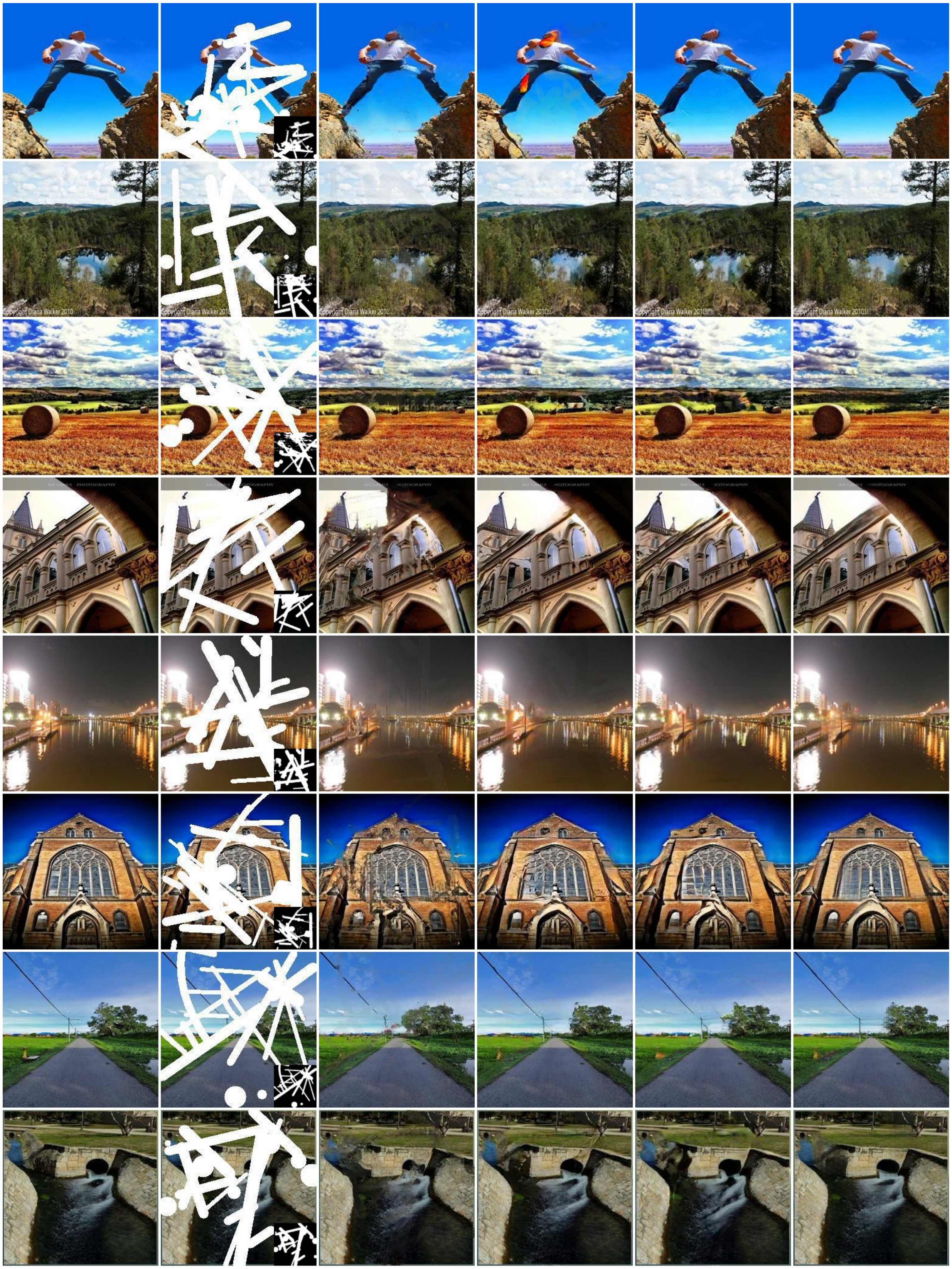


Figure 3. Qualitative Results on CelebA-HQ dataset with random mask. From left to right $a)$ Ground Truth, $b)$ Input Image, $c)$ Pluralistic (PICNet) [8], $d)$ GMCNN [5], $e)$ DeepFill-V2 [7], $f)$ Shift-Net (SN) [6], $g)$ Ours. All image are scaled to 256×256.



(a) Input Image (b) Ground Truth (c) Predicted (a) Input Image (b) Ground Truth (c) Predicted

Figure 4. Qualitative Results on Places2 dataset with center mask. From left to right $a)$ Input Image, $b)$ Ground Truth, $c)$ Ours. All image are scaled to 256×256.



a) GT b) Input Image c) PICNet d) GMCNN e) DeepFill-V2 f) Ours

Figure 5. Qualitative Results on Places2 dataset with random mask. From left to right $a)$ Ground Truth, $b)$ Input Image, $c)$ Pluralistic (PICNet) [8], $d)$ GMCNN [5], $e)$ DeepFill-V2 [7], $f)$ Ours. All image are scaled to 256×256.

Figure 6. Qualitative Results on Places2 dataset with random mask. From left to right $a)$ Ground Truth, $b)$ Input Image, $c)$ Pluralistic (PICNet) [8], $d)$ GMCNN [5], $e)$ DeepFill-V2 [7], $f)$ Ours. All image are scaled to 256×256.

(a) Input Image (b) Ground Truth (c) Predicted (a) Input Image (b) Ground Truth (c) Predicted

Figure 7. Qualitative Results on Paris Street View dataset with center mask. From left to right $a)$ Input Image, $b)$ Ground Truth, $c)$ Ours. All image are scaled to 256×256.

Figure 8. Qualitative Results on Paris Street View dataset with random mask. From left to right a) Input Image, b) Ground Truth, c) Ours. All image are scaled to 256×256.

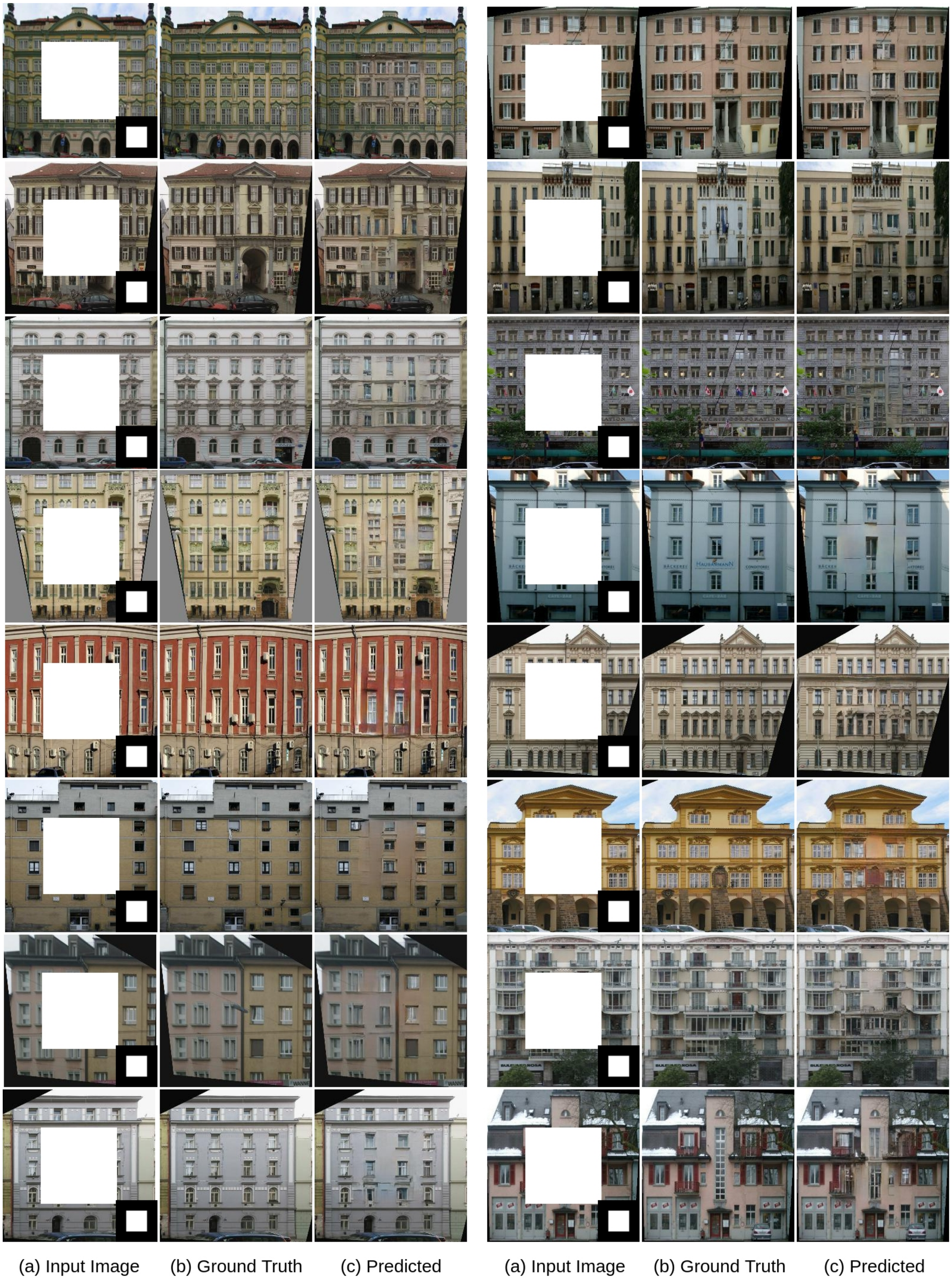


Figure 9. Qualitative Results on Facades dataset with center mask. From left to right $a)$ Input Image, $b)$ Ground Truth, $c)$ Ours. All image are scaled to 256×256.

(a) Input Image (b) Ground Truth (c) Predicted (a) Input Image (b) Ground Truth (c) Predicted

Figure 10. Qualitative Results on Facades dataset with random mask. From left to right $a)$ Input Image, $b)$ Ground Truth, $c)$ Ours. All image are scaled to 256×256.

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