

Learning to Learn Cropping Models for Different Aspect Ratio Requirements

Supplementary Material

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1. More Qualitative Results of the Proposed Method

During the inference, the model predicts the cropping area (intermediate result) according to the required aspect ratio at first and then obtains the final cropping result using a post-processing process. In this section, we show more intermediate and final cropping results in Figure 1 and Figure 2. These results show that the predicted area of the model for an image varies with the required aspect ratio, demonstrating that the proposed model can handle different aspect ratios adaptively. After the post-processing process, the obtained cropping results can effectively represent the original images while satisfying the aspect ratio requirements.

2. More Qualitative Comparison Results against State-of-the-art Methods

In this section, we present more qualitative comparison results against state-of-the-art methods. Following the main paper, we compare the proposed method with the VFN [2], A2RL [5], VPN [6], VEN [6], and GAIC [7] models. For a better comparison, we show more qualitative results of different methods on the HCDB [4], FCDB [1], and FAT [3] datasets using the same settings as the main paper. The results are presented in Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, and Figure 9.

References

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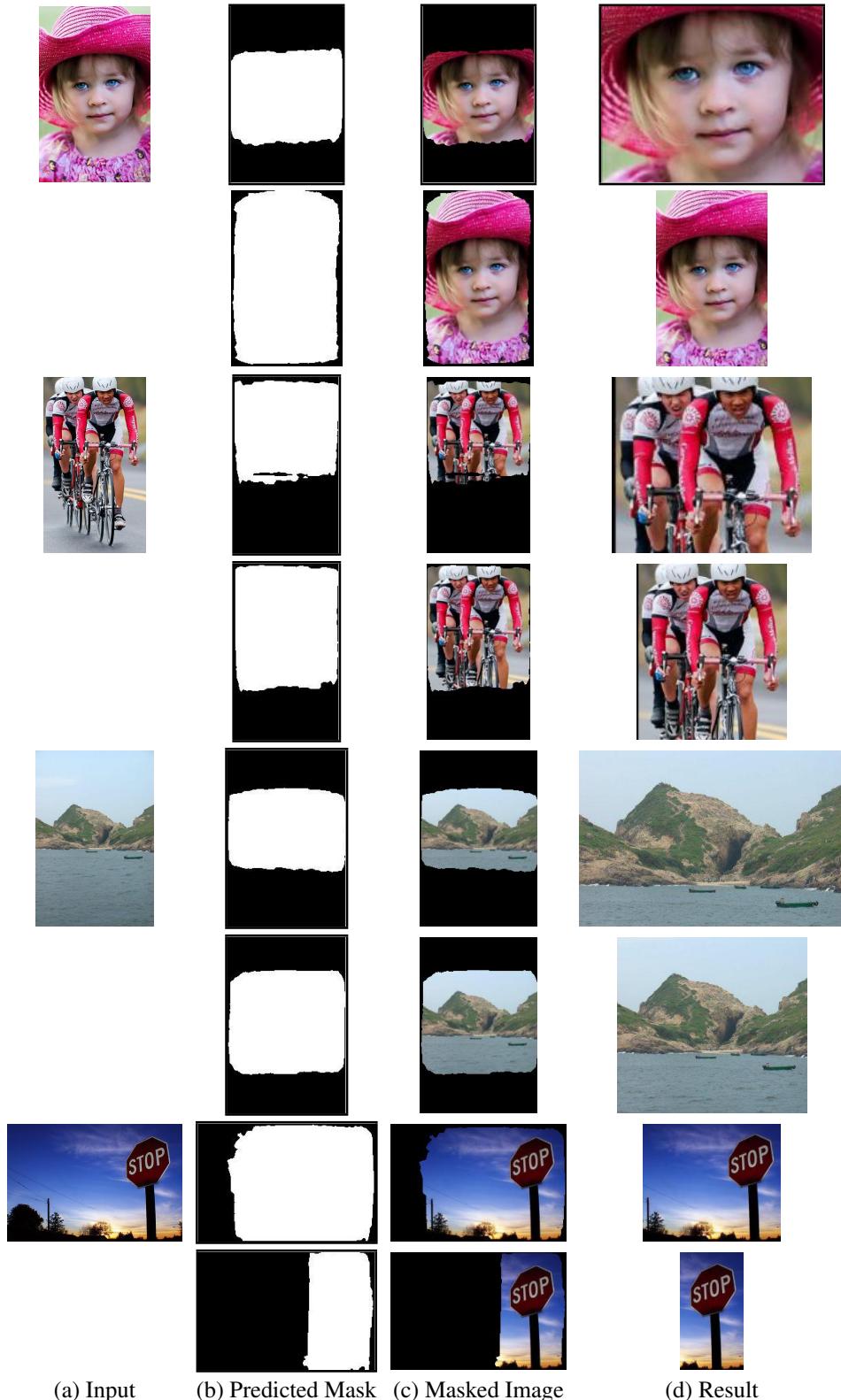
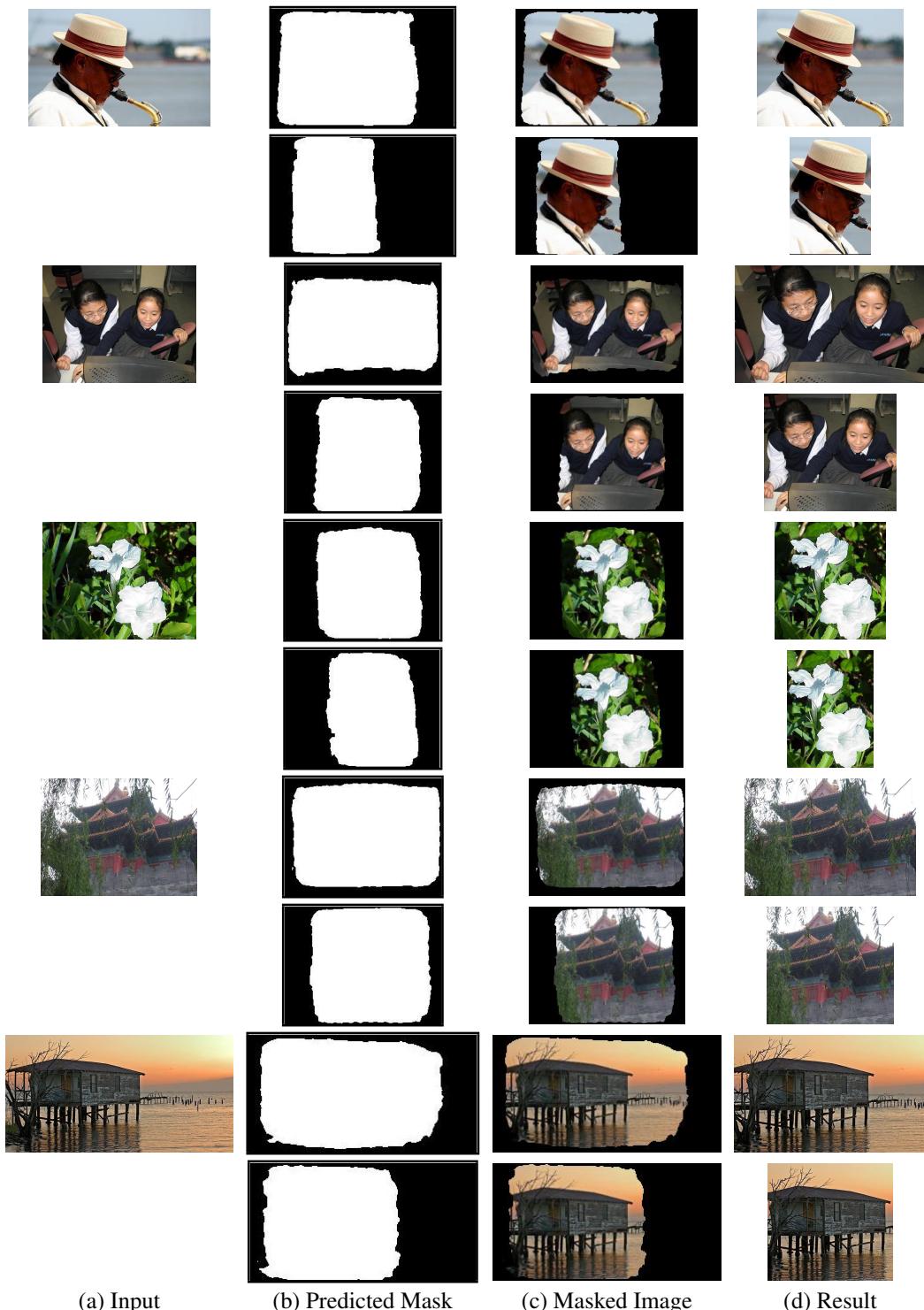


Figure 1. **Qualitative results of the proposed method.** In each group of images, the left one is the input image, the second column shows the predicted maps ($H_{out} \times W_{out} \times 1$) for different aspect ratio requirements, the third column shows the images masked by the predicted maps, and the fourth column shows the results satisfying the aspect ratio requirements after the post-processing.



(a) Input

(b) Predicted Mask

(c) Masked Image

(d) Result

Figure 2. **Qualitative results of the proposed method.** In each group of images, the left one is the input image, the second column shows the predicted maps ($H_{out} \times W_{out} \times 1$) for different aspect ratio requirements, the third column shows the images masked by the predicted maps, and the fourth column shows the results satisfying the aspect ratio requirements after the post-processing.

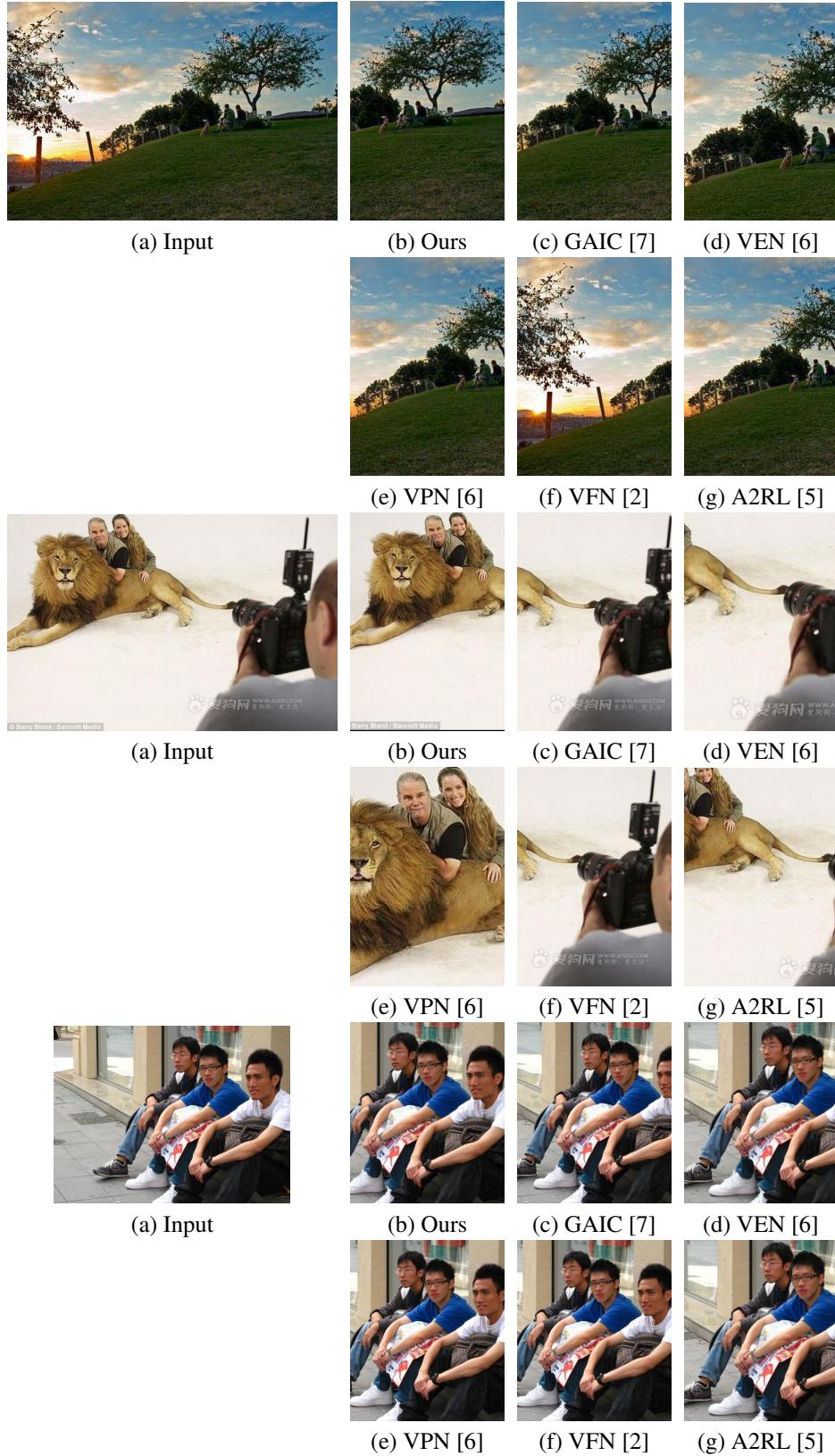


Figure 3. **Qualitative comparison results against state-of-the-art methods on the FAT [3] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.

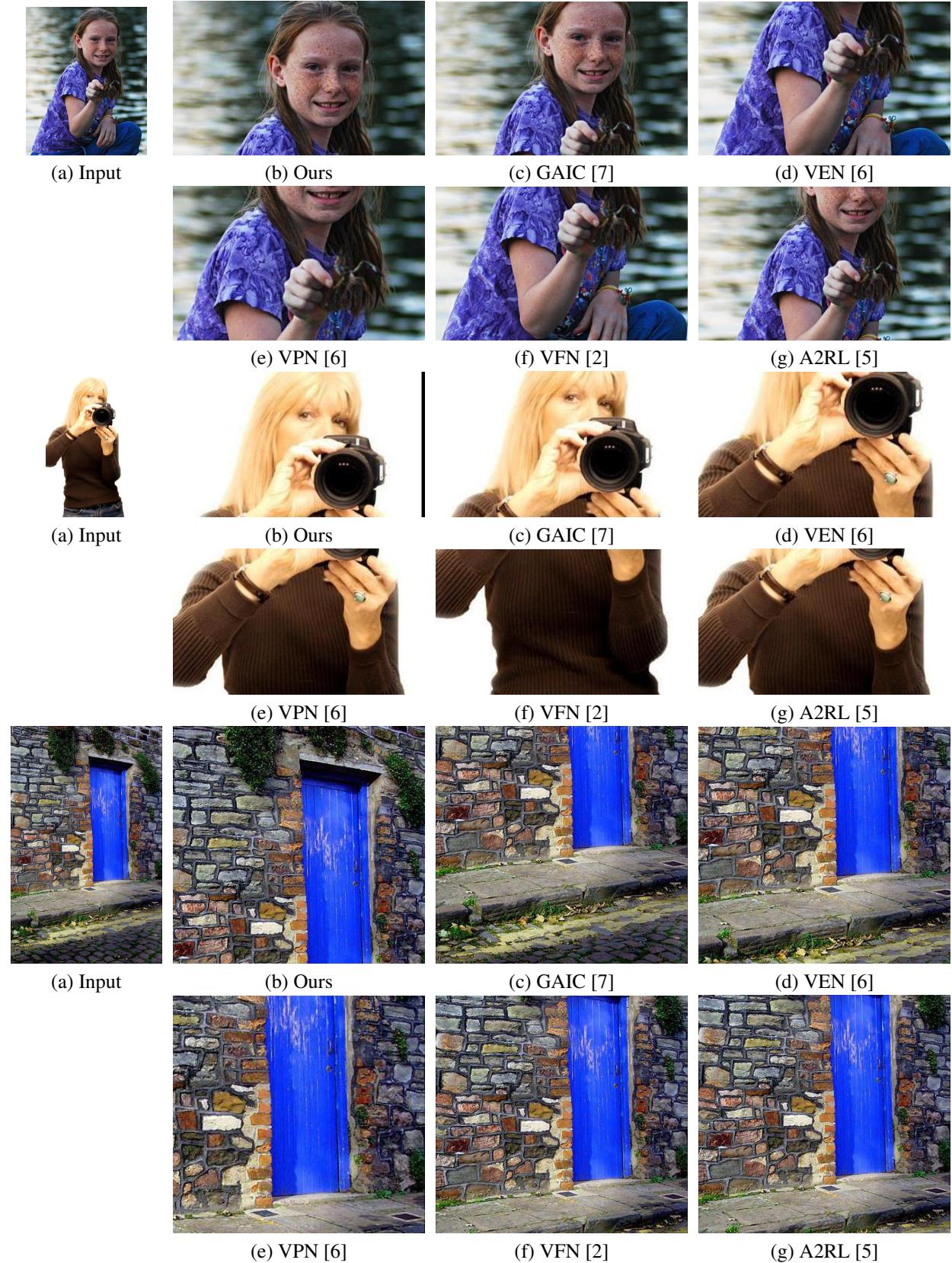


Figure 4. **Qualitative comparison results against state-of-the-art methods on the FAT [3] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.

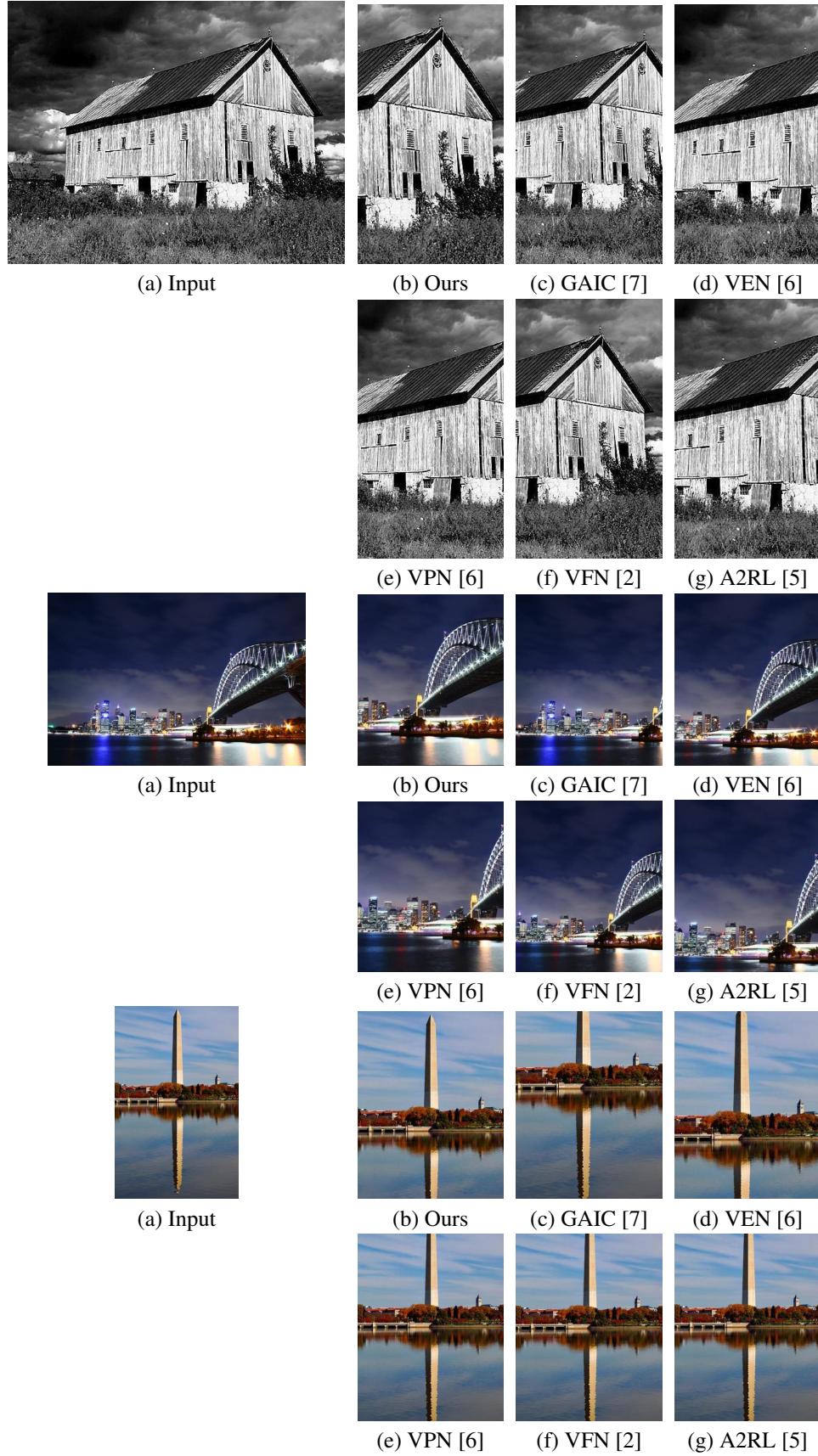


Figure 5. **Qualitative comparison results against state-of-the-art methods on the FAT [3] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.

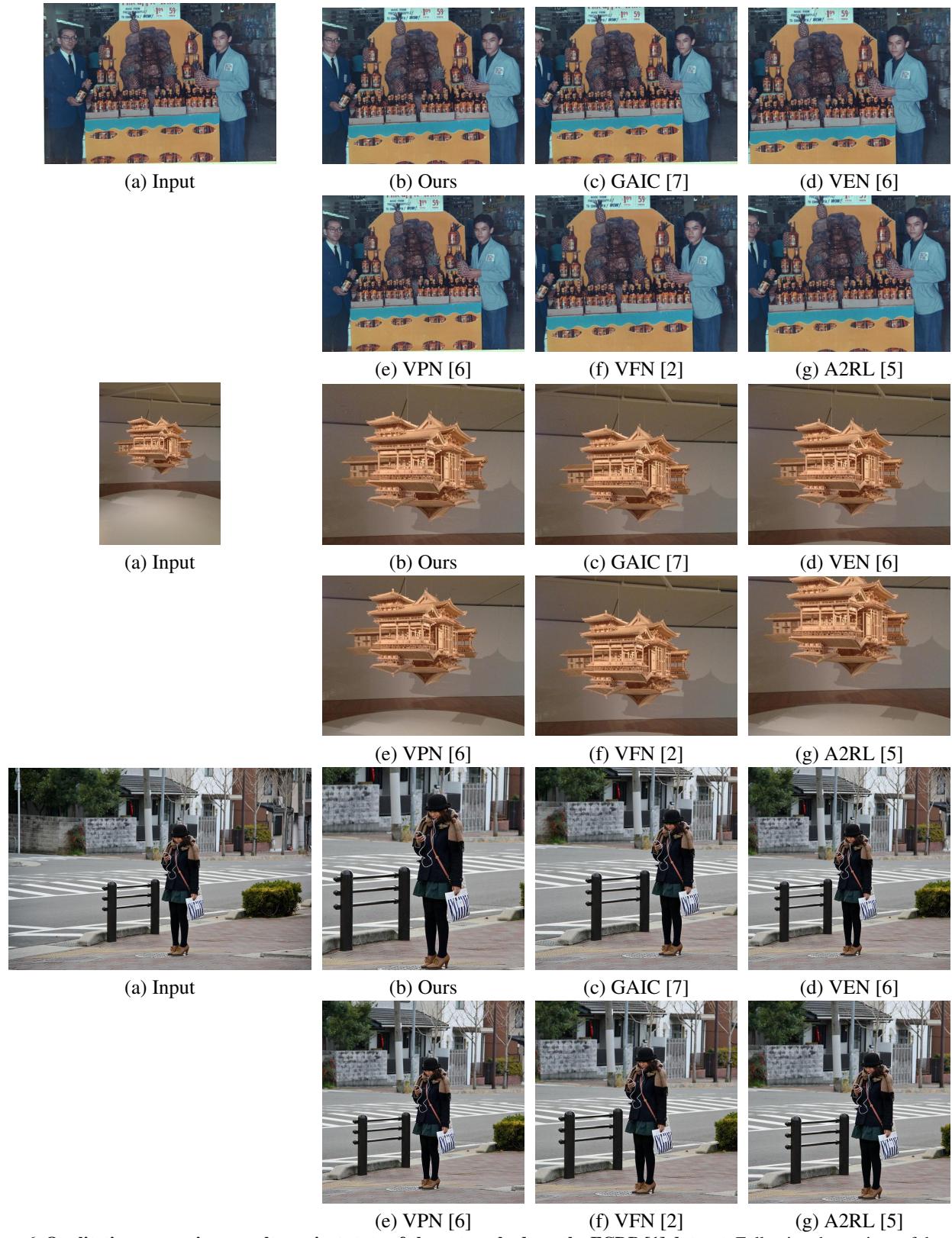


Figure 6. **Qualitative comparison results against state-of-the-art methods on the FCDB [1] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.

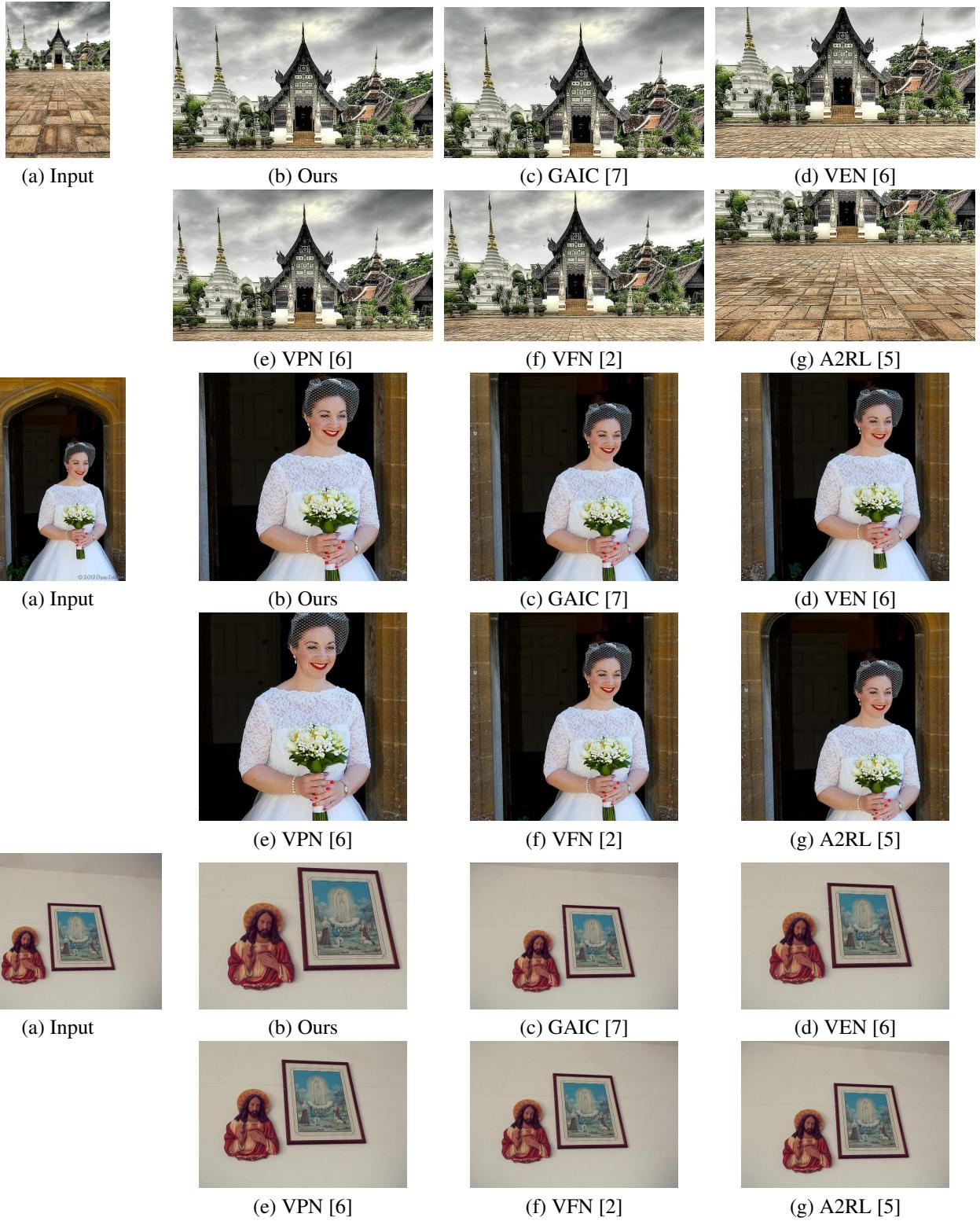


Figure 7. **Qualitative comparison results against state-of-the-art methods on the FCDB [1] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.

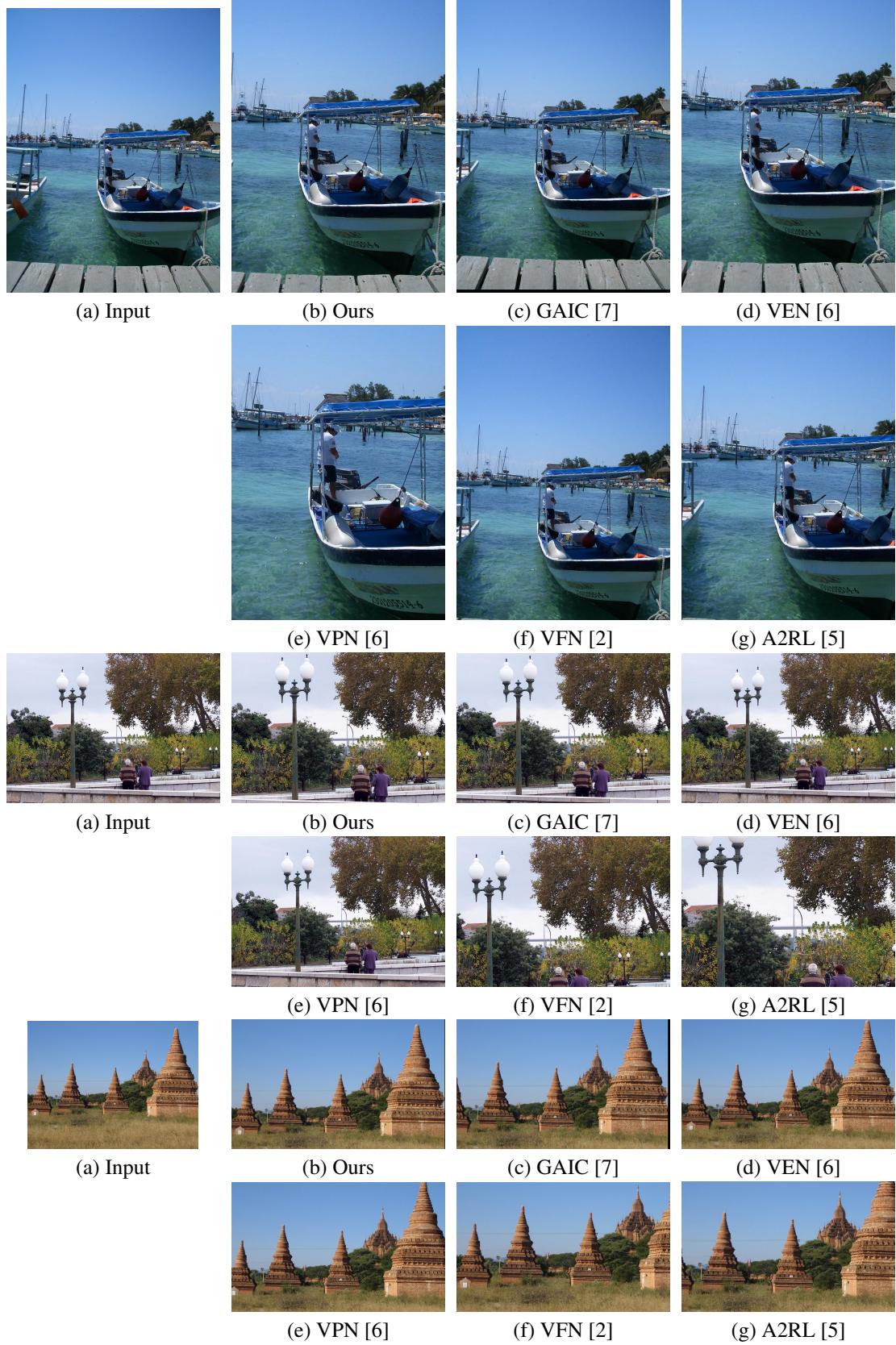


Figure 8. **Qualitative comparison results against state-of-the-art methods on the HCDB [4] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.

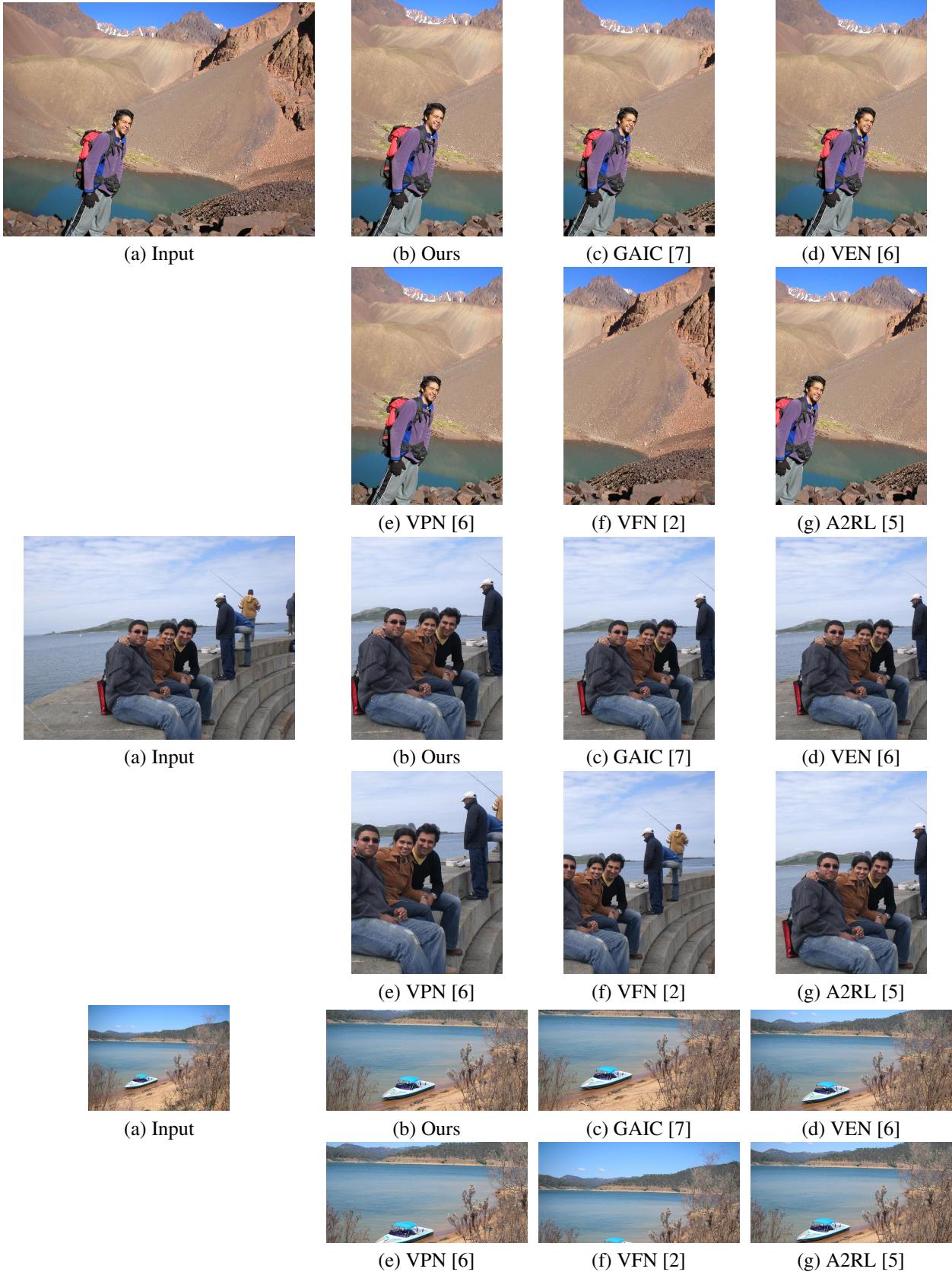


Figure 9. **Qualitative comparison results against state-of-the-art methods on the HCDB [4] dataset.** Following the settings of the main paper, we generate the cropping results of the specified aspect ratio using different methods for the qualitative comparison.