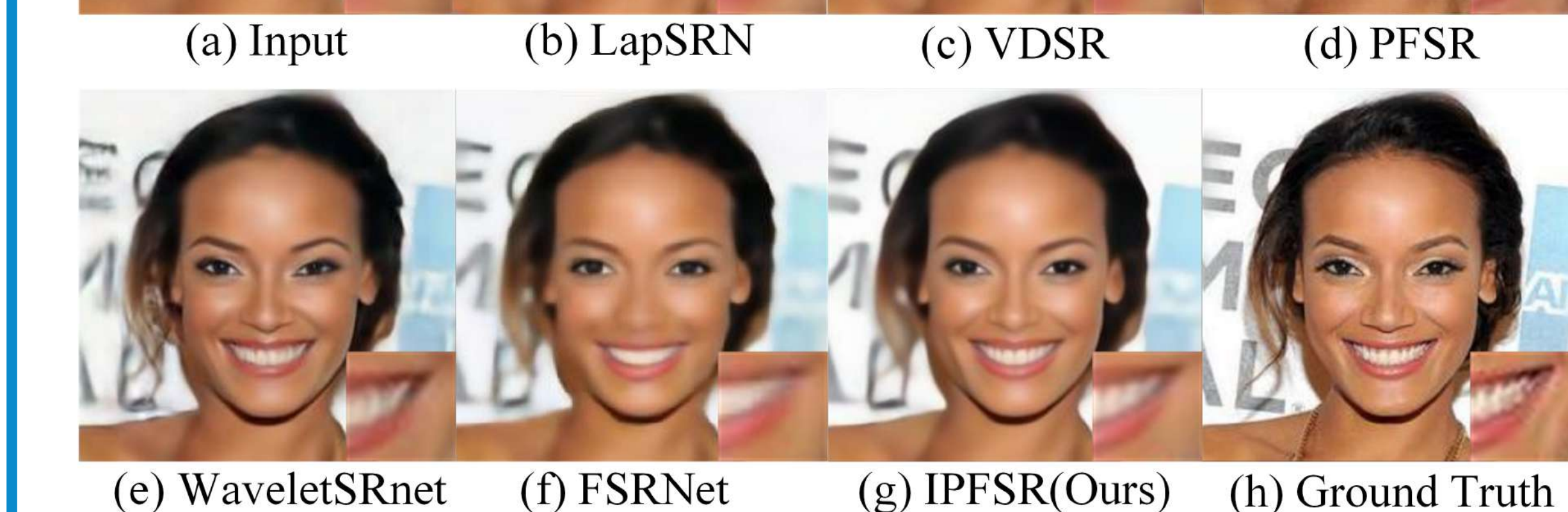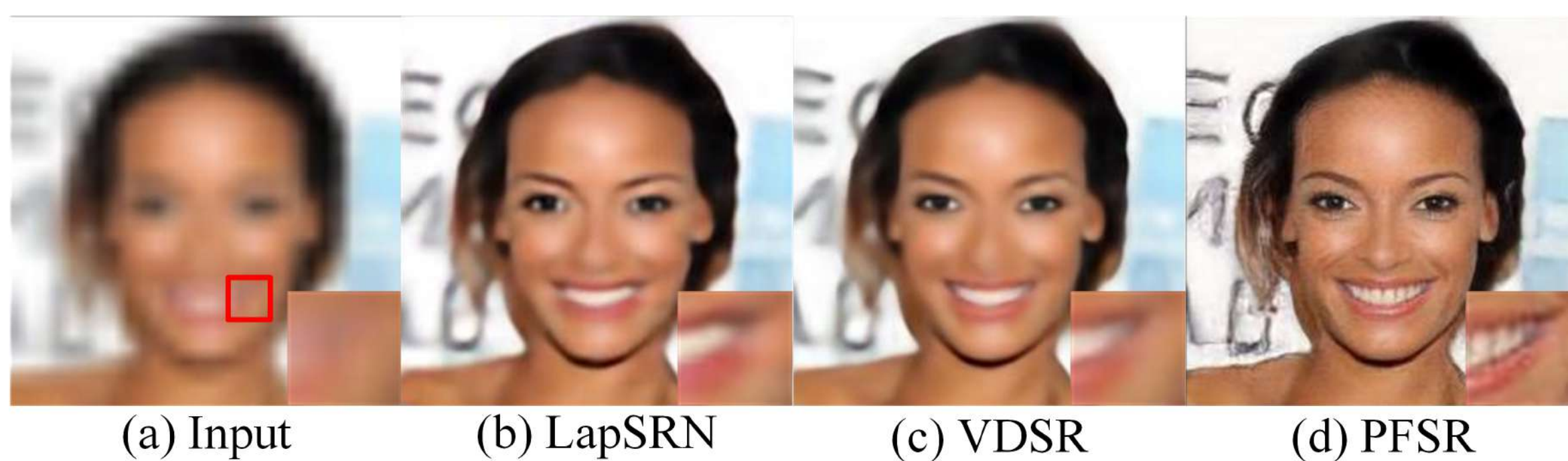# Face Super-Resolution Network with Incremental Enhancement of Facial Parsing Information

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1. Introduction

(a) Input   (b) LapSRN   (c) VDSR   (d) PFSR

(e) WaveletSRnet   (f) FSRNet   (g) IPFSR(Ours)   (h) Ground Truth

Motivation

- The prior knowledge of face images can effectively assist face image reconstruction.
- How to extract the prior information of low-resolution faces more effectively and how to fuse prior information to generate high magnification SR images are still problems worth further study.
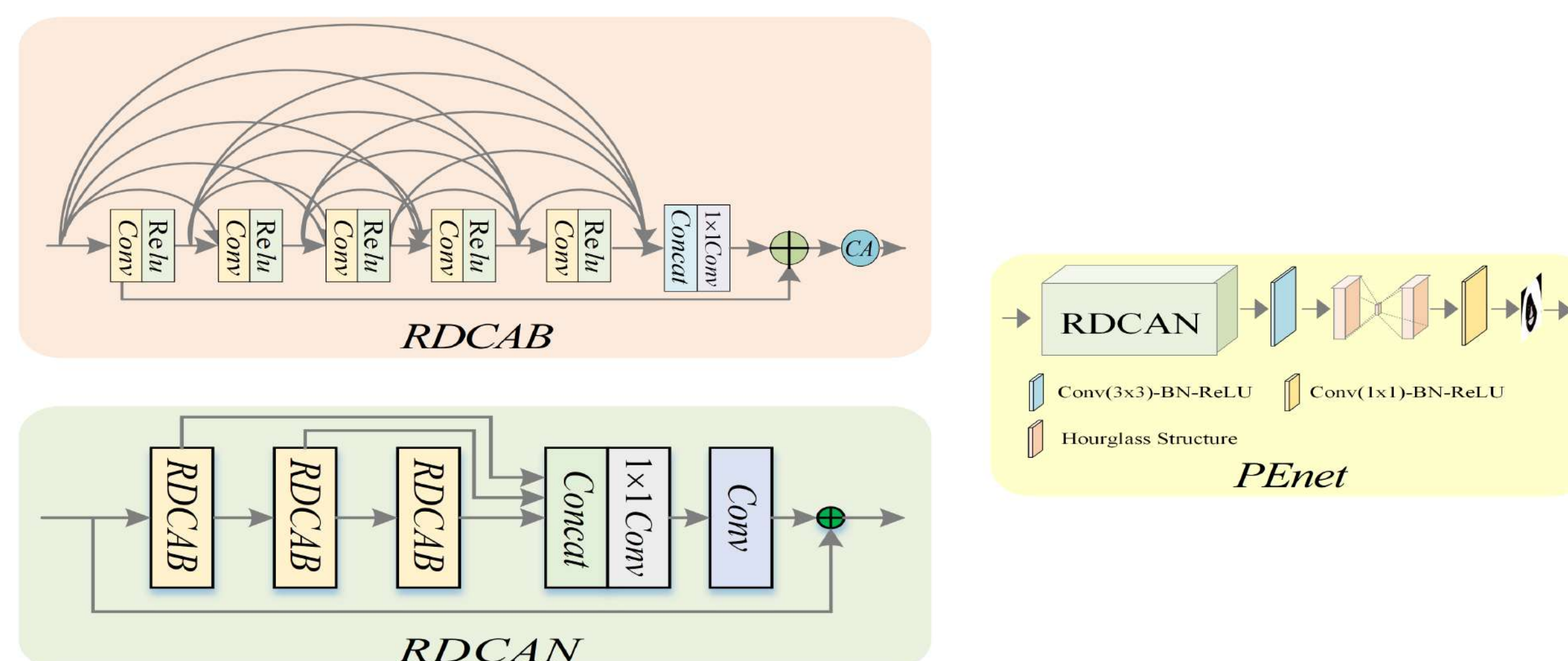
Contributions

- A multi-level parsing prior guided deep network is proposed for large factors face super-resolution.
- The prior prediction and image recovery processes are performed synergistically and progressively to improve image resolution.

2. Network Architecture

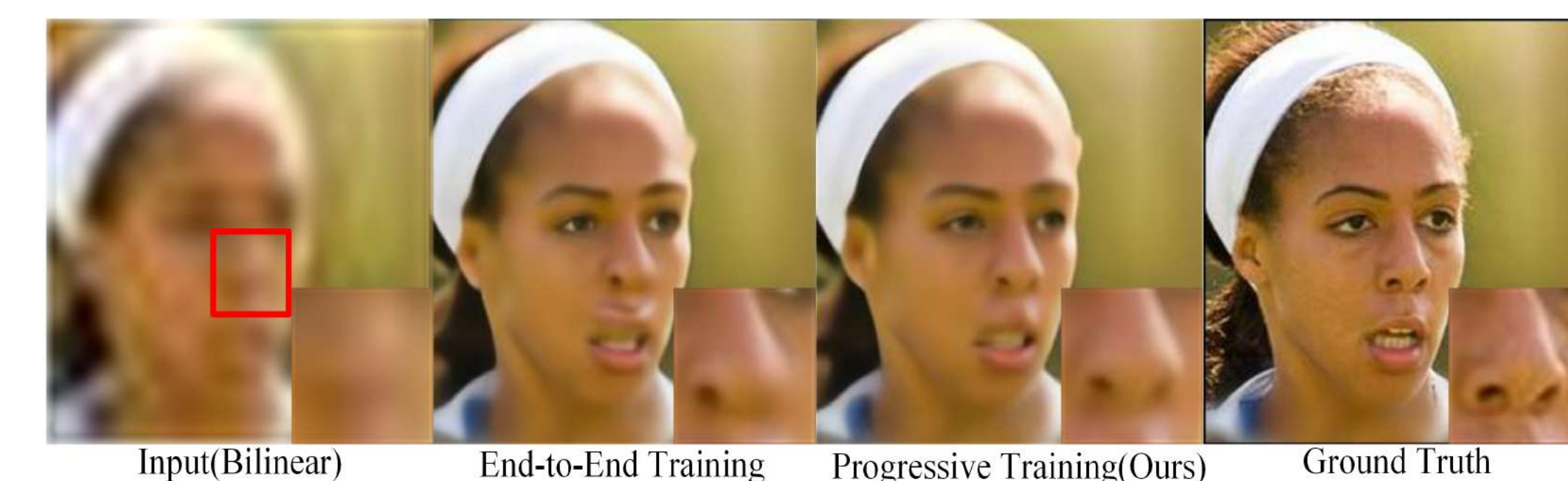### Overall Network Structure(IPFSR)
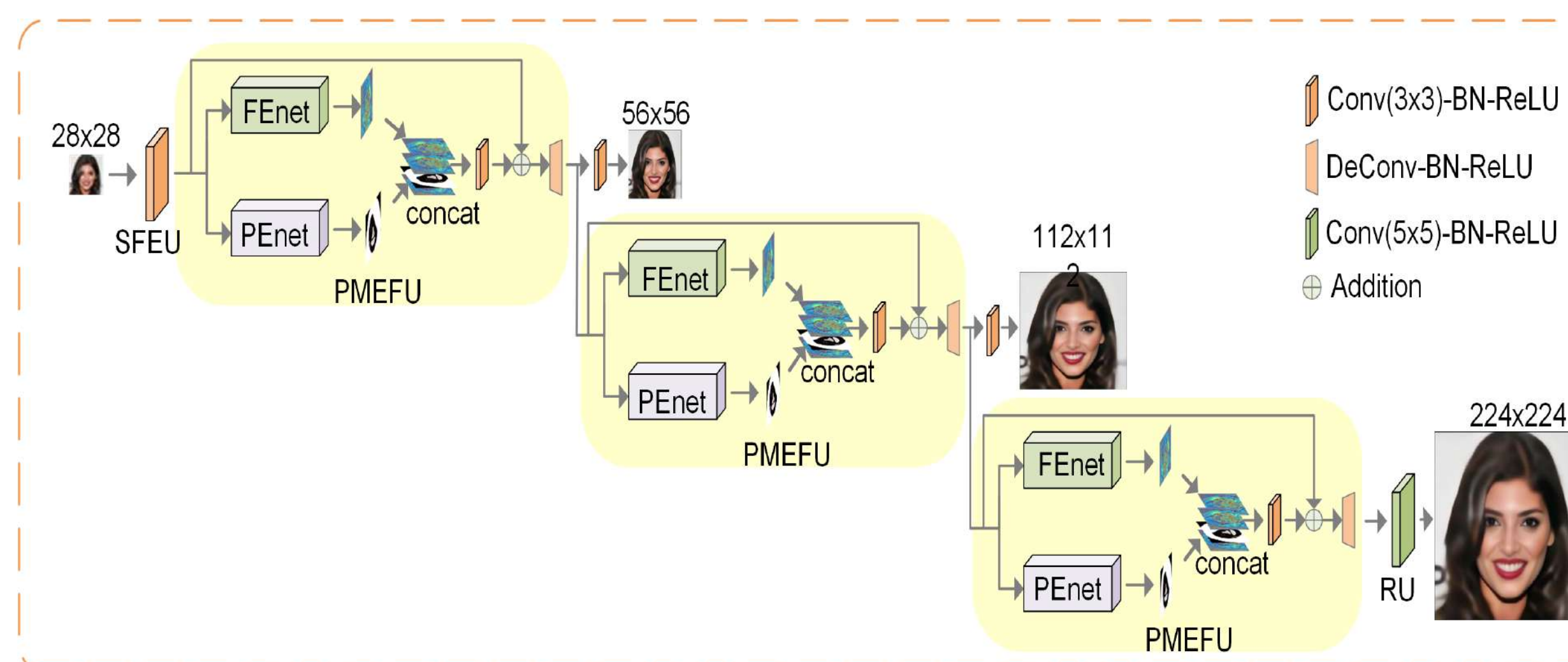
The Details of IPFSR

3. Discussions

Ablation Study

- Effectiveness of Progressive Training

	PSNR	SSIM	MS-SSIM
End-to-End Training	25.8753	0.7441	0.9271
Progressive Training	**26.1878**	**0.7543**	**0.9313**

Input(Bilinear)   End-to-End Training   Progressive Training(Ours)   Ground Truth

- The progressive training contributes to the improvement of network performance.
- Effectiveness of Different losses

Methods	PSNR	SSIM	MS-SSIM
Without parsing loss	26.1171	0.7533	0.9310
Without facial attention loss	26.1580	0.7537	0.9308
IPFSR(Ours)	**26.1878**	**0.7543**	**0.9313**

Input(Bilinear)   without parsing loss   without facial attention loss   IPFSR(Ours)

- With the help of different facial priors, the proposed IPFSR can achieve better face super-resolution performance.
- Effectiveness of Channel Attention

Methods	PSNR	SSIM	MS-SSIM
Without channel attention layer	26.1336	0.7541	0.9312
IPFSR(Ours)	**26.1878**	**0.7543**	**0.9313**

Input(Bilinear)   Without channel attention layer   IPFSR(Ours)   Ground Truth
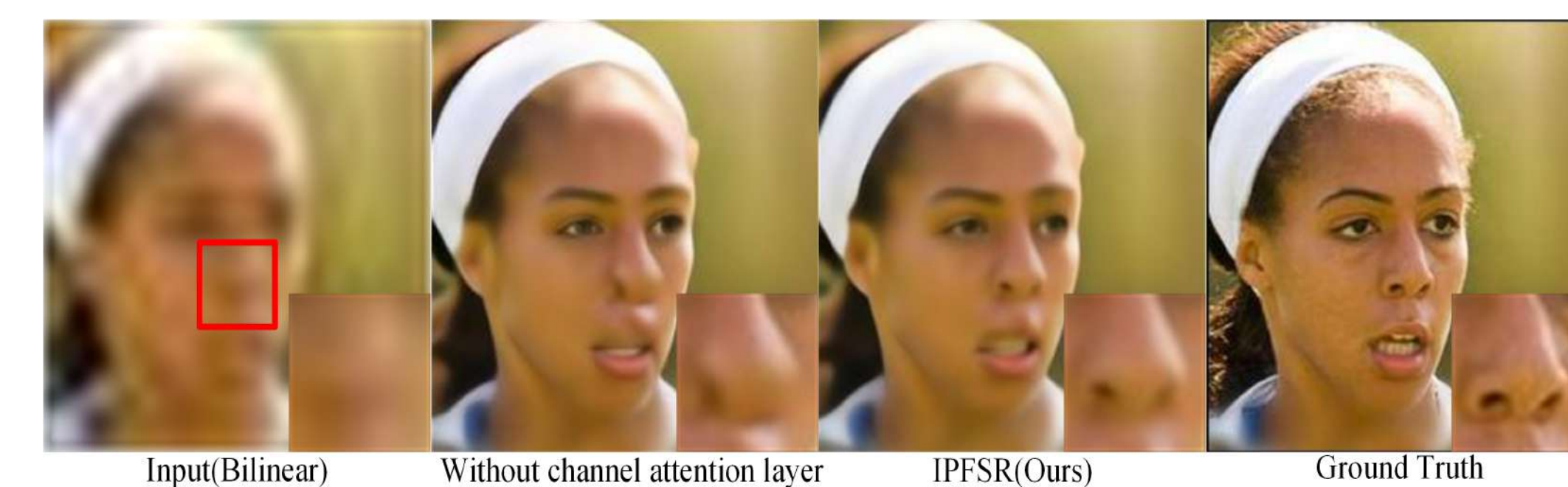
- The CA strategy is beneficial for focusing on learning facial features.

Model Size Analyses

Methods	LapSRN	PFSR	FSRNet	WSRnet	Ours
Para.	1.3M	9M	3.16M	75M	25.6M
PSNR/dB	25.2159	24.1507	25.2418	25.6154	**26.1878**

- The proposed method IPFSR can perform better on keeping a trade-off between the performance and model complexity.

## 4. Quantitative Results

Face Super-Resolution(PSNR/MS-SSIM)

Dataset	Bilinear	LapSRN	VDSR	PFSR	FSRNet	WaveletSR	IPFSR(Ours)
CelebAMask	22.4768/0.8208	25.2159/0.9161	25.4469/0.9178	24.1507/0.9012	25.2418/0.9193	25.6154/0.9270	**26.1878/0.9313**
Helen	23.7510/0.8478	26.5066/0.9302	26.9174/0.9333	24.7468/0.9096	25.6867/0.9269	25.8482/0.9283	**27.3433/0.9411**

5. Qualitative Results

Visual comparison on the CelebAMask-HQ dataset with a scaling factor of 8.

Input   LapSRN   VDSR   PFSR   FSRNet   WaveletSRnet   IPFSR(Ours)   Target
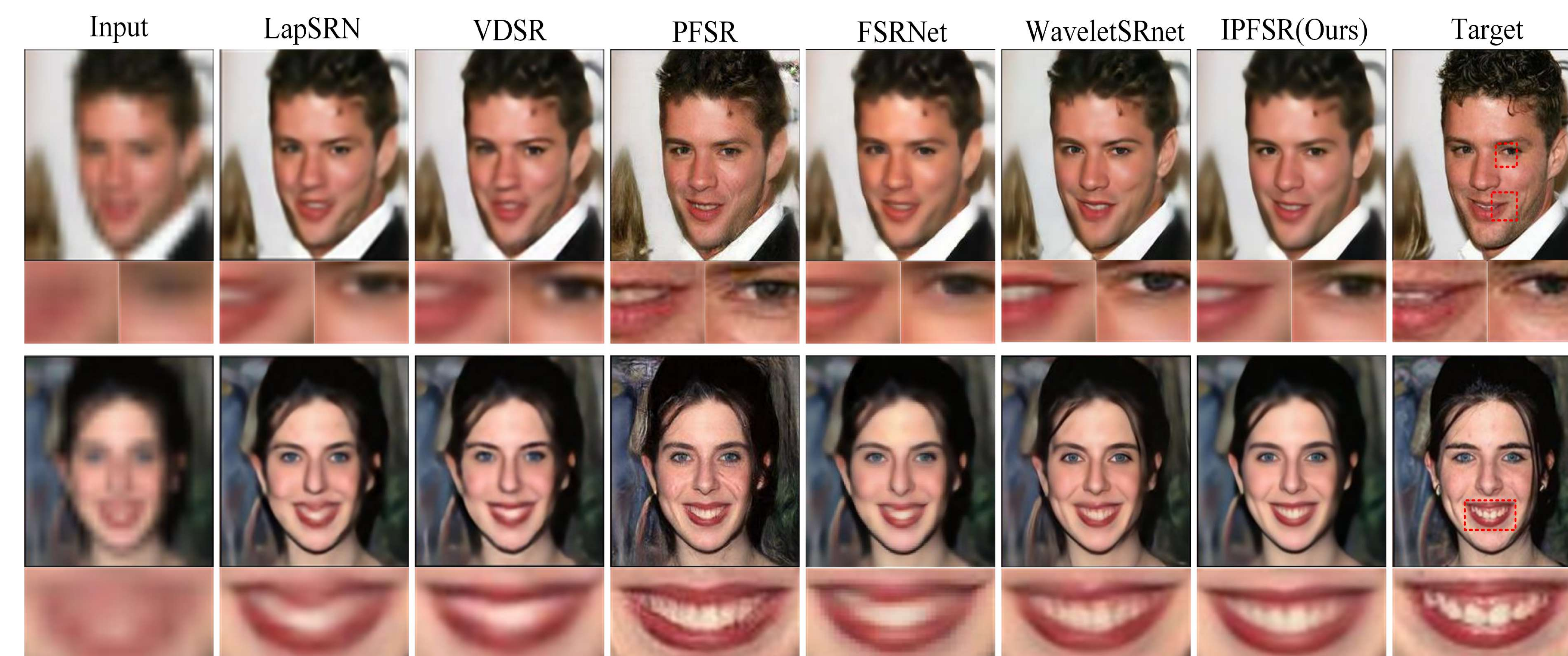
Visual comparison on the Helen dataset with a scaling factor of 8.

Input   LapSRN   VDSR   PFSR   FSRNet   WaveletSRnet   IPFSR(Ours)   Target
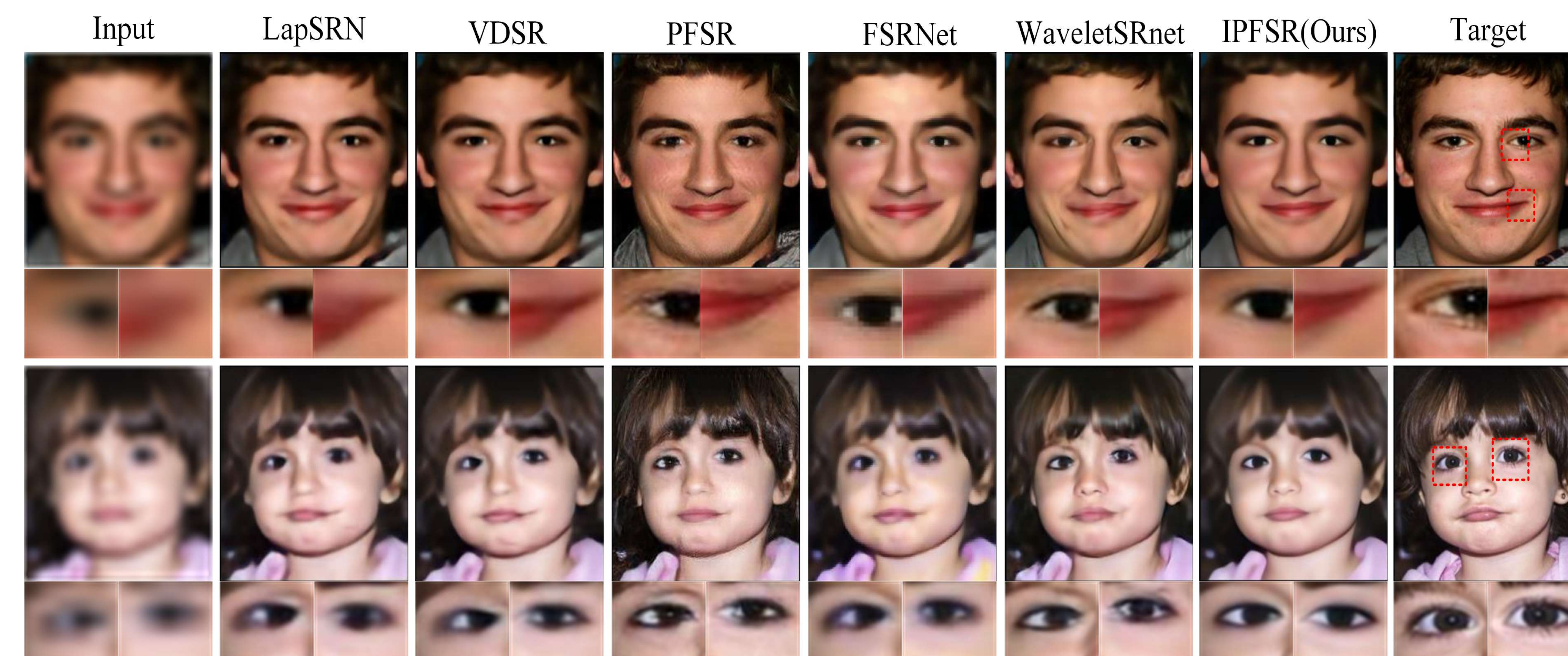
6. Conclusions

- A learning-based incremental boosting facial parsing approach is proposed for face super-resolution.
- Progressive strategy is introduced in both network model and training process to make prior prediction and image recovery processes synergistically and progressively to improve image resolution.
- Extensive experimental results have demonstrated that our method can achieve the great trade-off between SR image quality and network compactness.