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Dual Associated Encoder for Face Restoration

ICLR 2024

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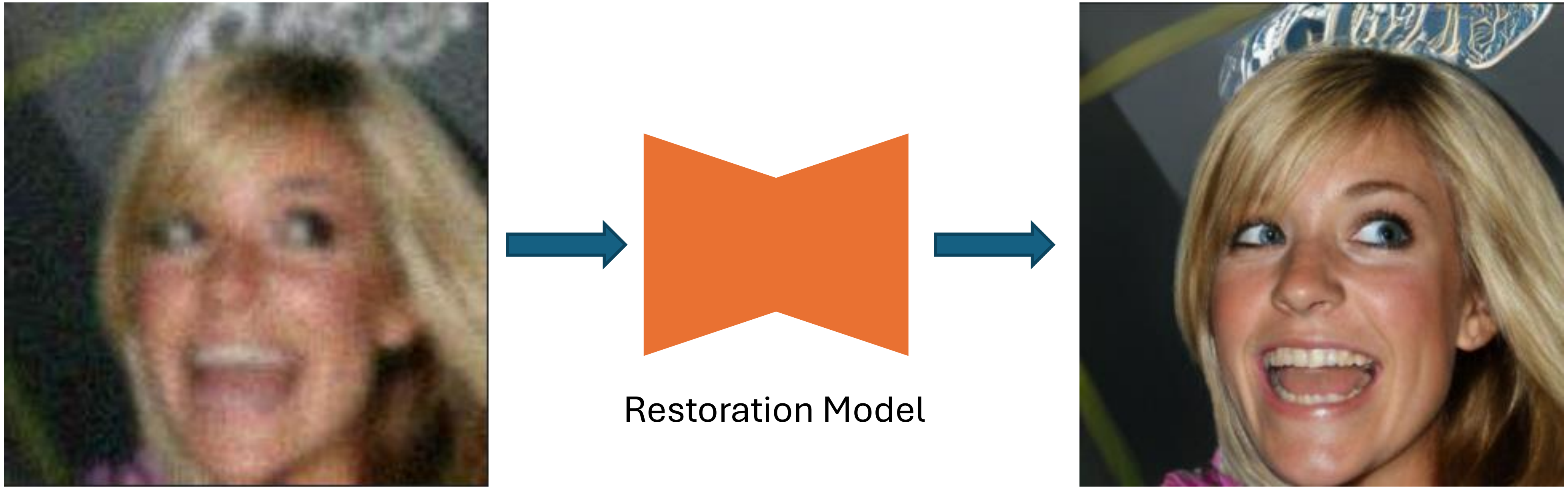
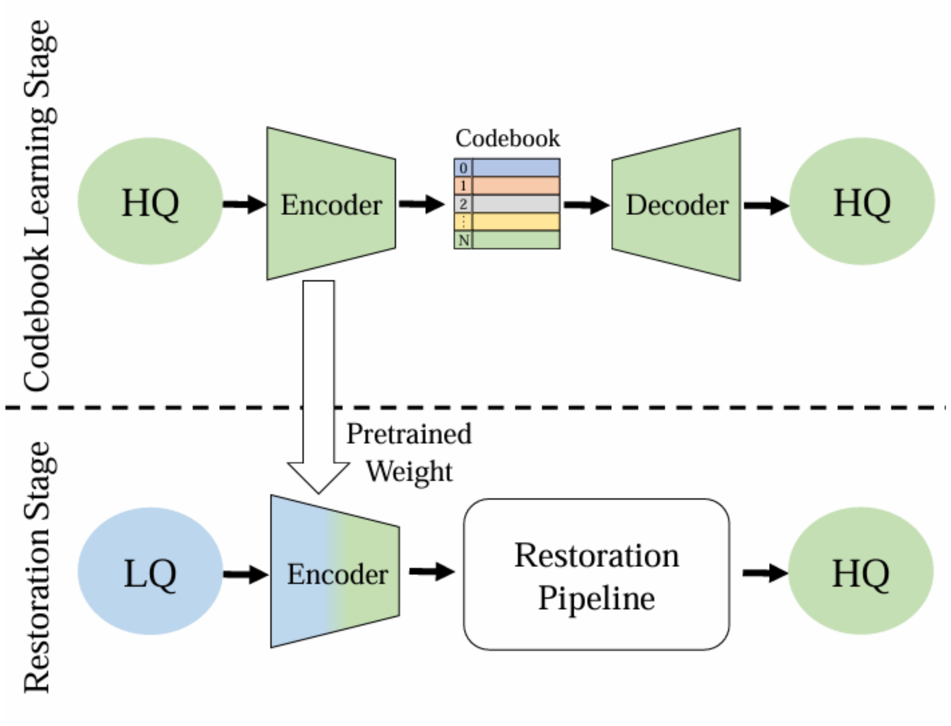
Problem Definition

- Blind Face Image Restoration
  - Input: severely degraded facial image
  - Target: Restore the low-quality input to high-quality output



Problem Observation

- Existing codebook prior approaches have two stages:
  - Codebook Learning Stage
  - Restoration Stage



Problem Observation

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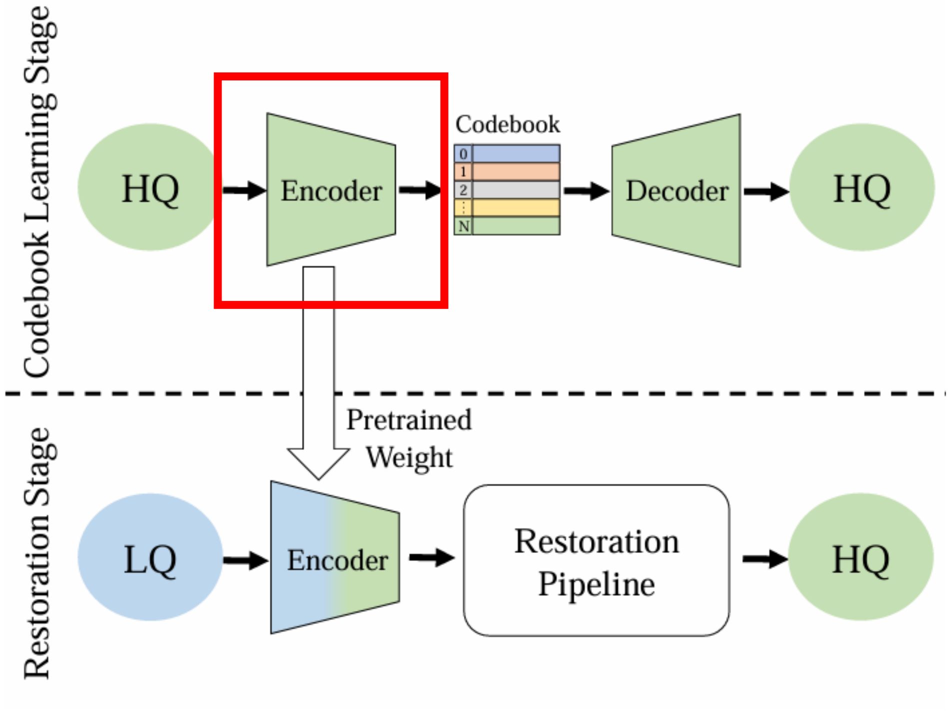
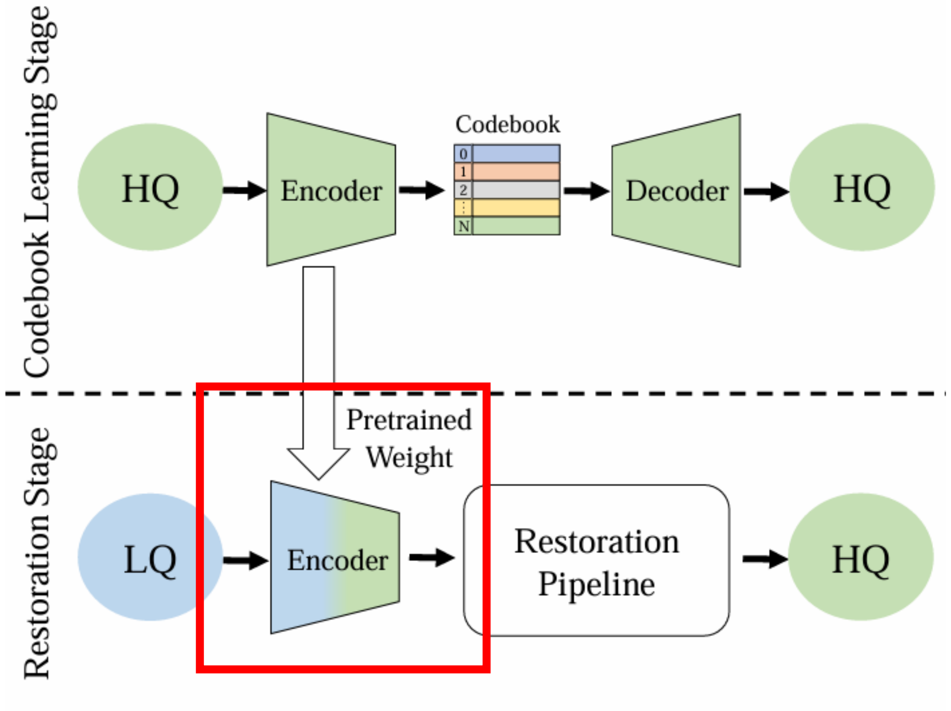
- Existing approaches rely on a **single encoder** pre-trained on HQ data.



Problem Observation

- Existing approaches rely on a **single encoder** pre-trained on HQ data.
- Encoding LQ inputs with **the same encoder** is insufficient, resulting in **imprecise feature representation** and **suboptimal performance**.



Our Proposed Algorithm

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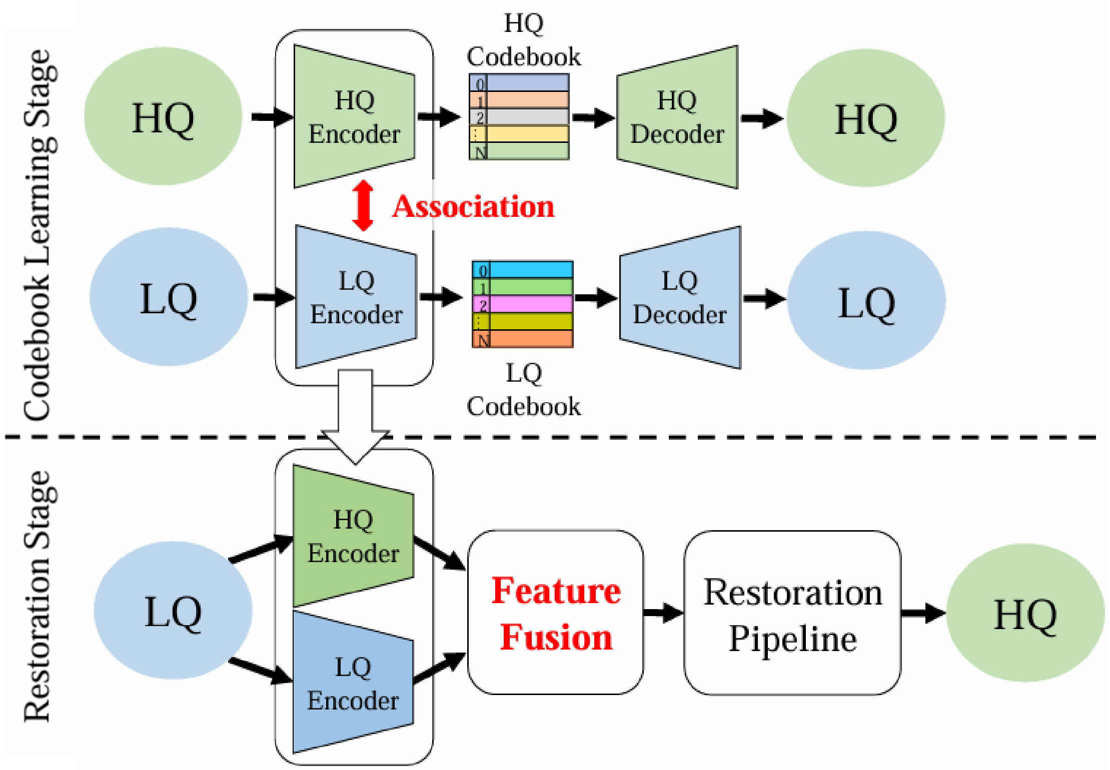
- We propose the integration of an **auxiliary branch** designed for encoding LQ information addressing domain bias and obtaining precise feature representation.



Our Proposed Algorithm

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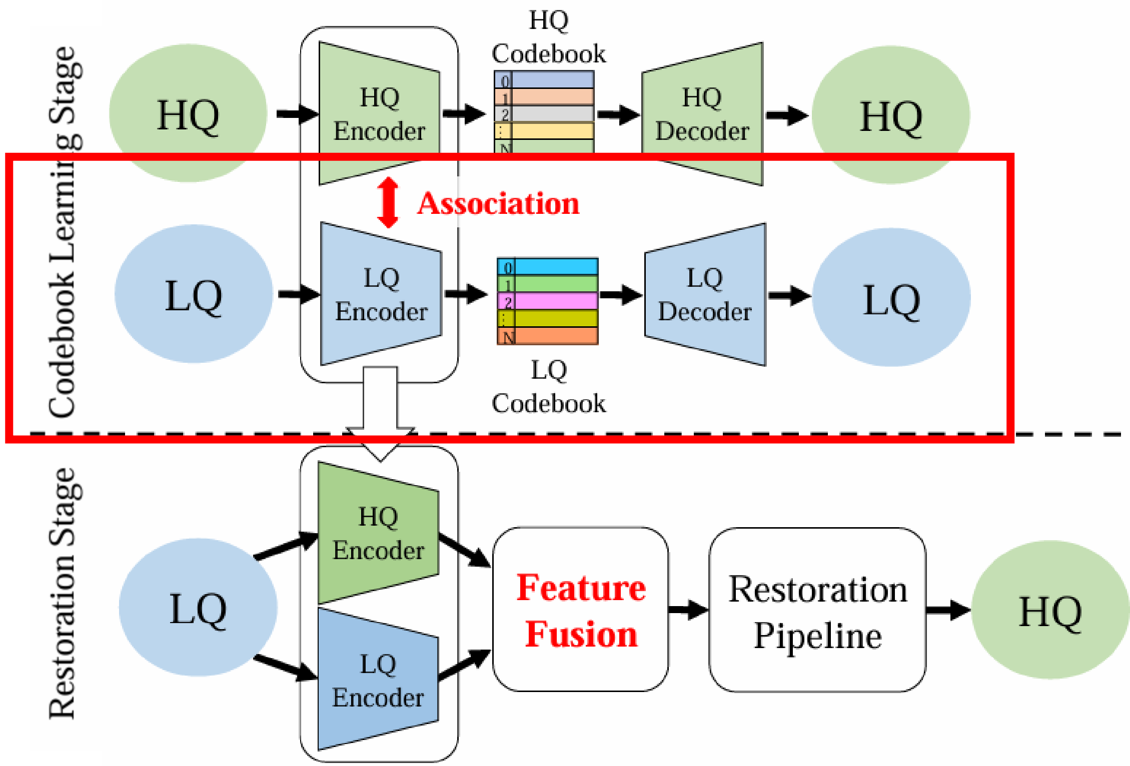

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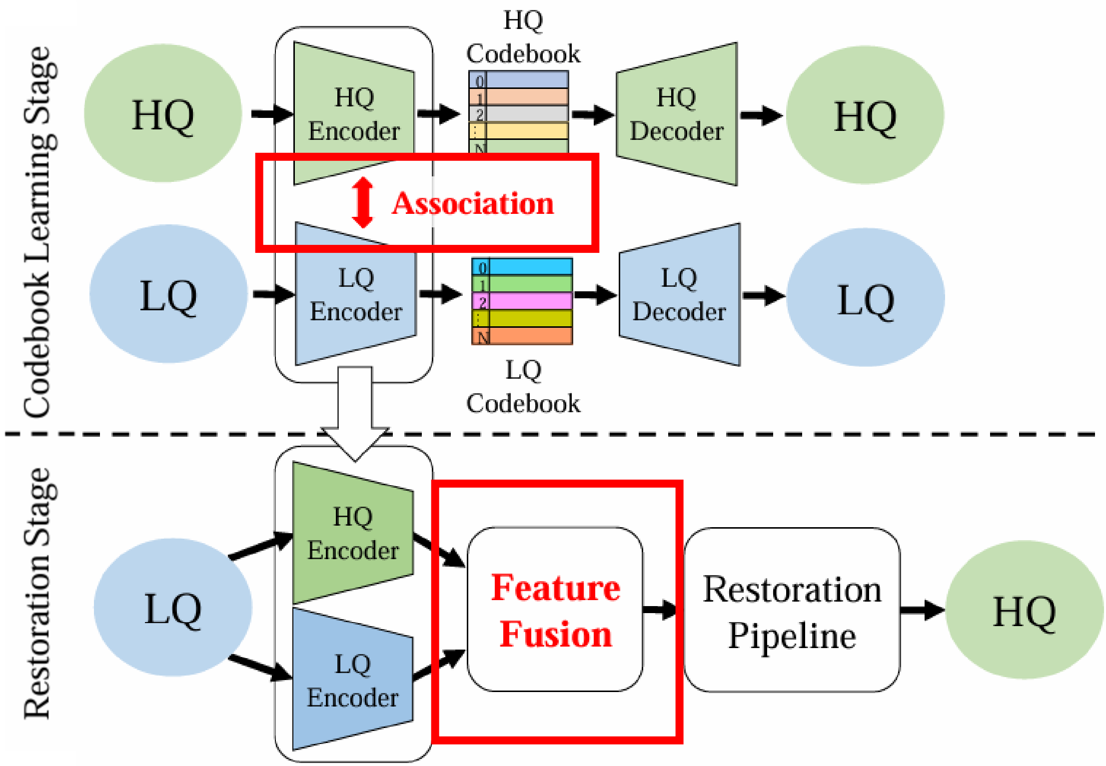
Our Proposed Algorithm

- Furthermore, we introduce an **association stage** and **feature fusion** module to enhance the integration of information from both encoders and assist our restoration pipeline.



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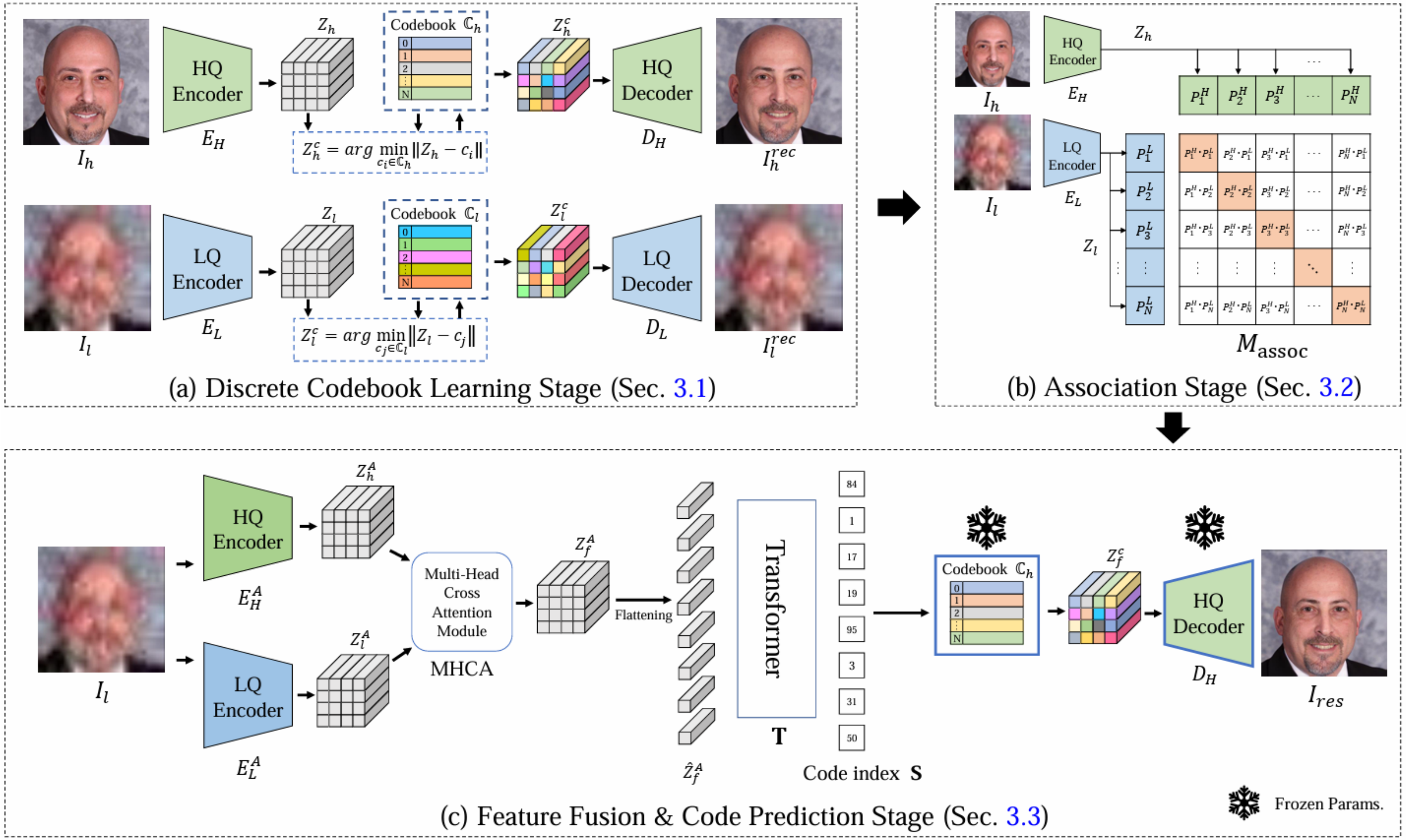
Our Proposed Algorithm

- Detailed network architecture of our algorithm



Our Proposed Algorithm

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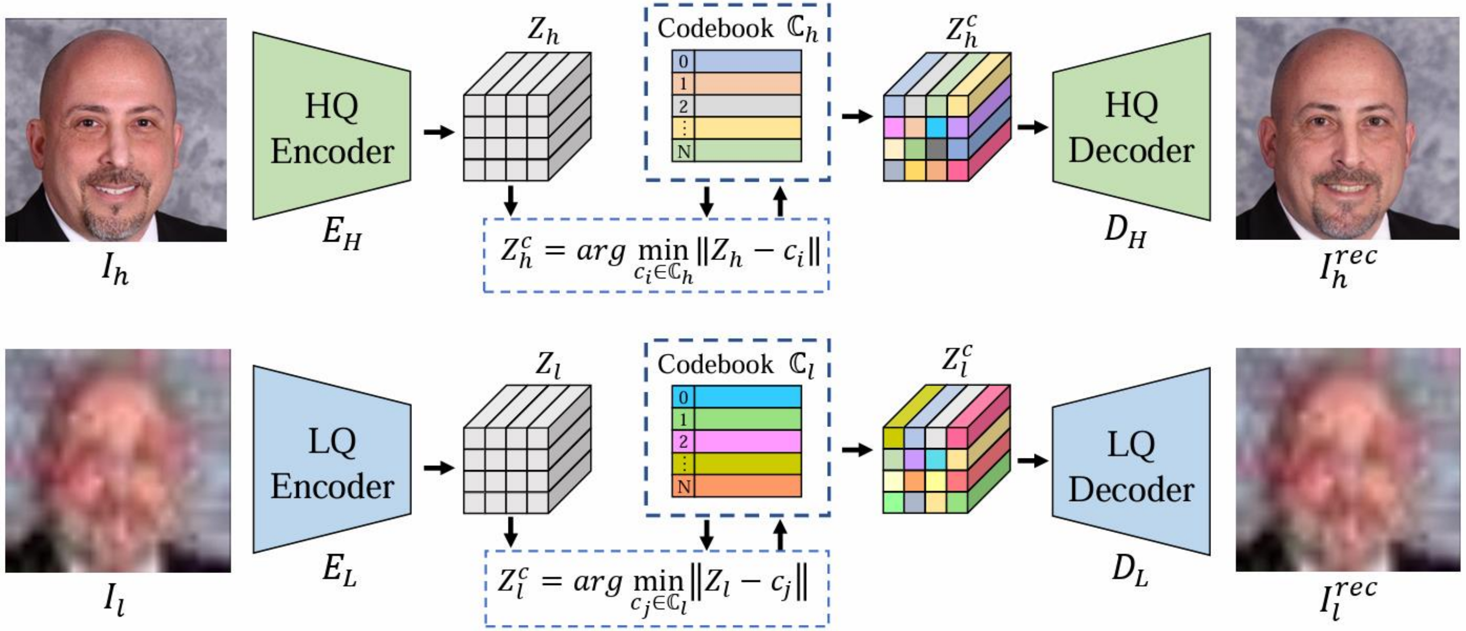
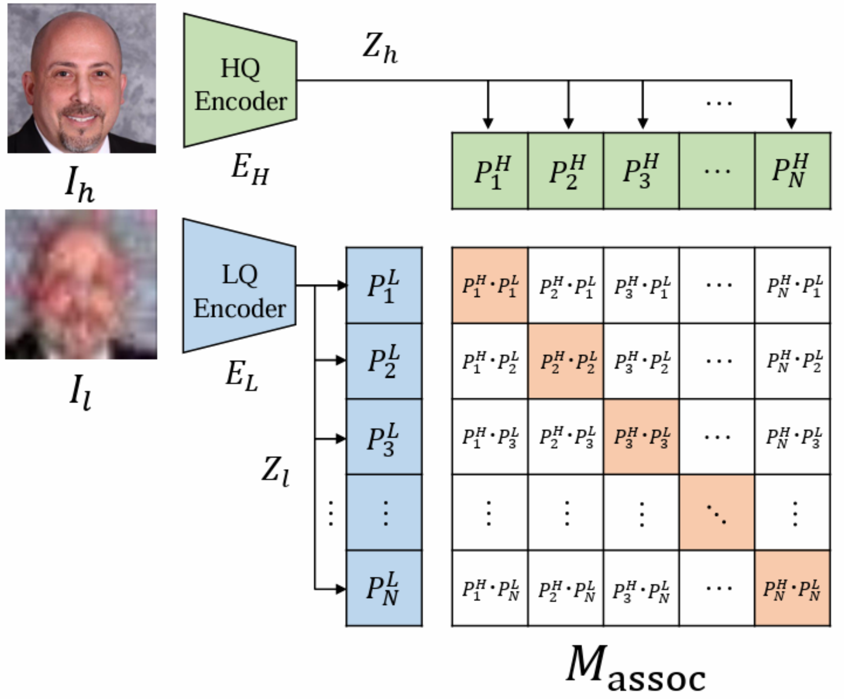
- Discrete codebook learning stage
- Goal: introduce an **auxiliary LQ encoder** to construct a **precise feature representation** and capture the LQ domain's **unique visual properties**.



Our Proposed Algorithm

- Association stage
- Goal: apply the **association strategy** to **reduce the domain gap** between the HQ and LQ domains, allowing the two encoders to encompass more information from both domains.



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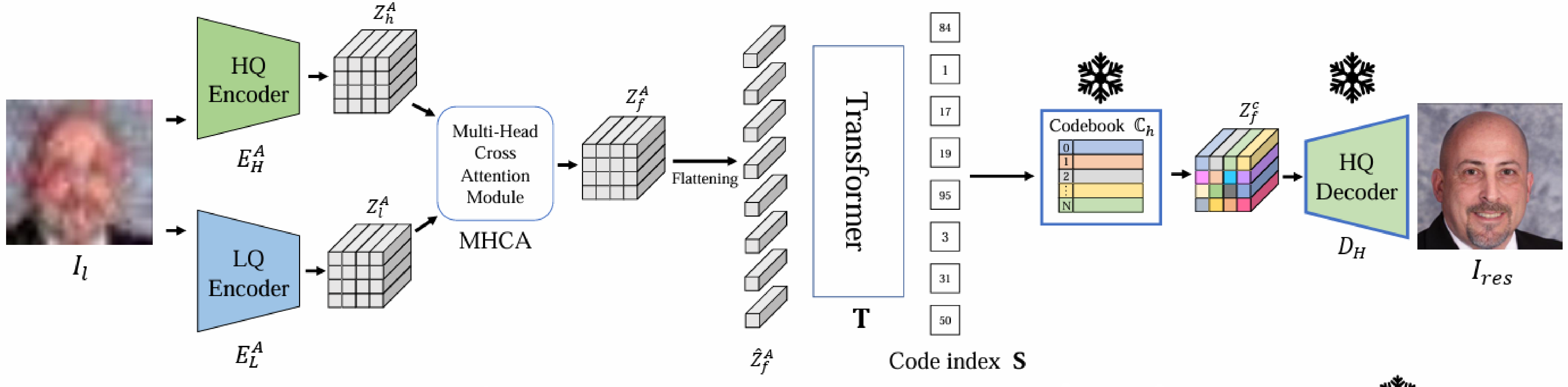
Our Proposed Algorithm

- Feature fusion and code prediction stage
- Goal: propose a **feature fusion module** to **mitigate the domain gap** and **information loss** and leverage the complementary aspects of the HQ and LQ domains, leading to **improved restoration results**.



Feature Fusion & Code Prediction Stage

Experimental Results

- Quantitative evaluation – Synthetic CelebA-Test [1]

Methods	FID↓	LPIPS↓	NIQE↓	IDA↓	LMD↓	PSNR↑	SSIM↑
Input	337.013	0.528	19.287	1.426	17.016	20.833	0.638
PSFRGAN	66.367	0.450	3.811	1.260	7.713	20.303	0.536
GFP-GAN	46.130	0.453	4.061	1.268	9.501	19.574	0.522
GPEN	55.308	0.425	3.913	1.141	7.259	20.545	0.552
RestoreFormer	54.395	0.467	4.013	1.231	8.883	20.146	0.494
CodeFormer	62.021	0.365	4.570	1.049	5.381	21.449	0.575
VQFR	54.010	0.456	3.328	1.237	9.128	19.484	0.472
DR2	63.675	0.409	5.104	1.215	7.890	20.327	0.595
DAEFR (Ours)	52.056	0.388	4.477	1.071	5.634	19.919	0.553

[1] Karras, Tero, et al. "Progressive Growing of GANs for Improved Quality, Stability, and Variation." *International Conference on Learning Representations*. 2018.

Experimental Results

- Quantitative evaluation – Real-world datasets [1][2][3]

Dataset / Methods	LFW-Test FID↓	LFW-Test NIQE↓	WIDER-Test FID↓	WIDER-Test NIQE↓	BRIAR-Test FID↓	BRIAR-Test NIQE↓
Input	137.587	11.003	199.972	13.498	201.061	10.784
PSFRGAN	49.551	4.094	49.857	4.033	196.774	3.979
GFP-GAN	50.057	3.966	39.730	3.885	97.360	5.281
GPEN	51.942	3.902	46.359	4.104	91.653	5.166
RestoreFormer	48.412	4.168	49.839	3.894	107.654	5.064
CodeFormer	52.350	4.482	38.798	4.164	98.134	5.018
VQFR	50.712	3.589	44.158	3.054	92.072	4.970
DR2	46.550	5.150	45.726	5.188	96.968	5.417
DAEFR (Ours)	47.532	3.552	36.720	3.655	90.032	4.649

[1] Huang, Gary B., et al. "Labeled faces in the wild: A database for studying face recognition in unconstrained environments." Workshop on faces in 'Real-Life' Images: detection, alignment, and recognition. 2008.
[2] Yang, Shuo, et al. "Wider face: A face detection benchmark." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.
[3] Cornett, David, et al. "Expanding accurate person recognition to new altitudes and ranges: The briar dataset." Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2023.

Experimental Results

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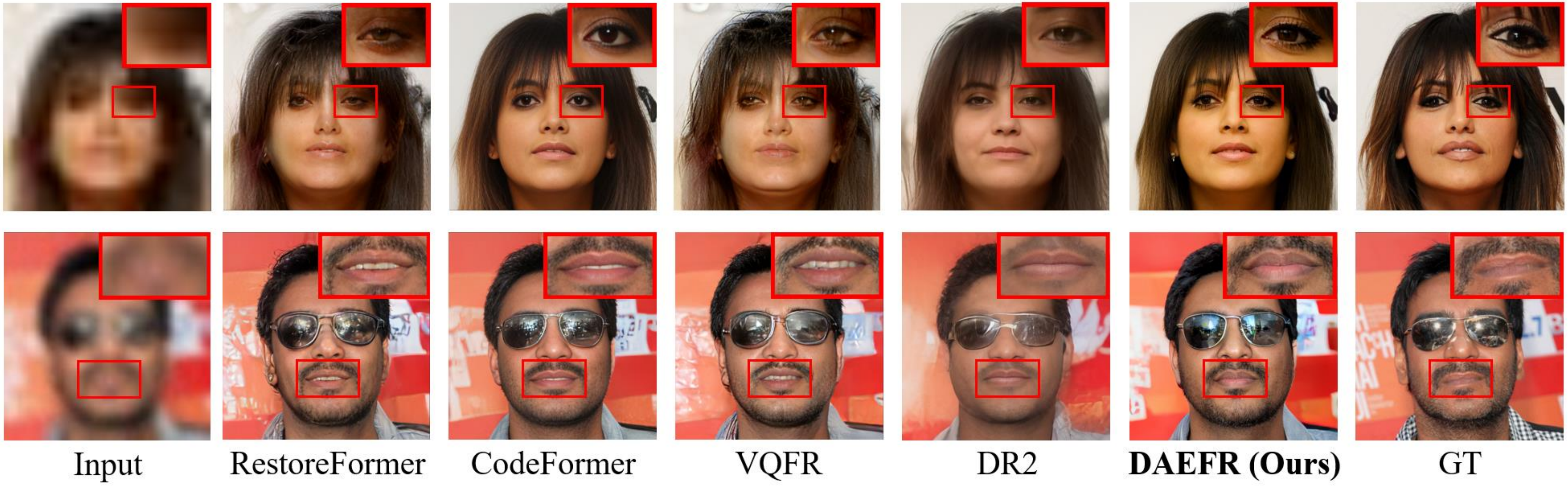
- CelebA-Test



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Experimental Results

- LFW-Test

Input RestoreFormer CodeFormer VQFR DR2 **DAEFR (Ours)**

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Experimental Results

- WIDER-Test

Input RestoreFormer CodeFormer VQFR DR2 **DAEFR (Ours)**

Conclusion

- We introduce an auxiliary LQ encoder to construct a more precise feature representation that captures the unique visual characteristics and statistical properties in the LQ domain.
- By incorporating information from hybrid domains, our association and feature fusion methods effectively use the representation from HQ and LQ domains and address the challenge of the domain gap.
- Our DAEFR addresses the challenging face restoration problem under severe degradation. We demonstrate its effectiveness with SoTA quantitative and qualitative performances.

Thanks for your listening!

Our Project Page: https://liagm.github.io/DAEFR/