

7 SUPPLEMENTARY MATERIALS

7.1 IMPLEMENTATION DETAILS

We build our work on top of 2DQuant’s open sourced repository [Liu et al. \(2024\)](#), and use SwinIR-light [Liang et al. \(2021\)](#) as the model backbone of our method. For the Hadamard transform and statistical tests, we use SciPy [Virtanen et al. \(2020\)](#). For finetuning, we use the Adam [Kinga et al. \(2015\)](#) optimizer with a learning rate of $1 * 10^{-2}$ and betas set to (0.9, 0.999). We clip all gradient values to between $[-1, 1]$ and we finetune for at most 4000 iterations, or until we reach a nan gradient which we handle by safely exiting. We select the model with the highest PSNR and SSIM. For measuring the time and space complexity of our model, we calculate inference time in seconds and size of model parameters in MB. Our code is written with PyTorch [Paszke et al. \(2019\)](#) and runs for at most 7 hours on one NVIDIA RTX 6000 48G GPU. The anonymous open source code for this paper along with instructions can be found [here](#).

7.2 RESULTS

Method ($\times 2$)	Bit	Set5		Set14		B100		Urban100		Manga109	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SwinIR-light	32	38.15	0.9611	33.86	0.9206	32.31	0.9012	32.76	0.9340	39.11	0.9781
Bicubic	32	32.25	0.9118	29.25	0.8406	28.68	0.8104	25.96	0.8088	29.17	0.9128
PTQ4ViT	4	37.43	0.9571	33.19	0.9139	31.84	0.8950	31.54	0.9212	37.59	0.9735
NoisyQuant	4	37.50	0.9570	33.06	0.9101	31.73	0.8936	31.31	0.9181	37.47	0.9723
2DQuant	4	37.87	0.9594	33.41	0.9161	32.02	0.8971	31.84	0.9251	38.31	0.9761
CondiQuant	4	38.03	0.9605	33.50	0.9180	32.16	0.8993	32.03	0.9282	38.57	0.9769
CompSRT (ours)	4	38.13	0.9610	33.81	0.9203	32.28	0.9009	32.57	0.9325	38.98	0.9778
PTQ4ViT	3	36.49	0.9510	32.49	0.9045	31.27	0.8854	30.16	0.9027	36.41	0.9673
NoisyQuant	3	35.32	0.9334	31.88	0.8911	30.73	0.8710	29.28	0.8835	35.30	0.9537
2DQuant	3	37.32	0.9567	32.35	0.9106	31.60	0.8911	30.45	0.9086	37.24	0.9722
CondiQuant	3	37.77	0.9594	33.21	0.9151	31.94	0.8966	31.18	0.9197	38.01	0.9755
CompSRT (ours)	3	38.11	0.9609	33.82	0.9202	32.27	0.9008	32.53	0.9321	38.90	0.9775
PTQ4ViT	2	33.25	0.8923	30.22	0.8402	29.21	0.8066	27.31	0.8111	32.75	0.9093
NoisyQuant	2	30.13	0.7620	28.80	0.7536	28.26	0.7421	26.68	0.7627	30.40	0.8204
2DQuant	2	36.00	0.9497	31.98	0.9012	30.91	0.8810	28.62	0.8819	34.40	0.9602
CondiQuant	2	37.15	0.9567	32.74	0.9103	31.55	0.8912	29.96	0.9047	36.63	0.9713
CompSRT (ours)	2	38.03	0.9605	33.70	0.9194	32.19	0.9294	32.22	0.9294	38.69	0.9770

Table 6: Performance comparison with SOTA methods for scale factor ($\times 2$) across different bit widths. All comparative results are taken from SwinIR-light [Liang et al. \(2021\)](#), PTQ4ViT [Yuan et al. \(2024\)](#), NoisyQuant [Liu et al. \(2023\)](#), 2DQuant [Liu et al. \(2024\)](#), and CondiQuant [Liu et al. \(2025\)](#). Our method achieves superior performance across all datasets and bitwidths.

Method ($\times 3$)	Bit	Set5		Set14		B100		Urban100		Manga109	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SwinIR-light	32	34.63	0.9290	30.54	0.8464	29.20	0.8082	28.66	0.8624	33.99	0.9478
Bicubic	32	29.54	0.8516	27.04	0.7551	26.78	0.7187	24.00	0.7144	26.16	0.8384
PTQ4ViT	4	33.77	0.9201	29.75	0.8272	28.62	0.7942	27.43	0.8361	32.50	0.9360
NoisyQuant	4	33.13	0.9122	29.06	0.8093	27.93	0.7754	26.66	0.8143	31.94	0.9293
2DQuant	4	34.06	0.9231	30.12	0.8374	28.89	0.7988	27.69	0.8405	32.88	0.9389
CondiQuant	4	34.32	0.9260	30.29	0.8417	29.05	0.8039	28.05	0.8506	33.23	0.9431
CompSRT (ours)	4	34.56	0.9284	30.49	0.8454	29.17	0.8075	28.50	0.8598	33.83	0.9467
PTQ4ViT	3	32.75	0.9028	29.14	0.8113	28.06	0.7712	26.43	0.8014	31.20	0.9131
NoisyQuant	3	30.78	0.8511	27.94	0.7624	26.98	0.7153	25.43	0.7481	29.64	0.8792
2DQuant	3	33.24	0.9135	29.56	0.8255	28.50	0.7873	26.65	0.8116	31.46	0.9235
CondiQuant	3	33.92	0.9224	30.02	0.8367	28.84	0.7986	27.37	0.8356	32.48	0.9367
CompSRT (ours)	3	34.54	0.9281	30.48	0.8451	29.16	0.8070	28.47	0.8589	33.79	0.9465
PTQ4ViT	2	29.96	0.7901	27.36	0.7030	26.74	0.6590	24.56	0.6460	27.37	0.7390
NoisyQuant	2	27.53	0.6641	25.77	0.5952	25.37	0.5613	23.59	0.5739	26.03	0.6632
2DQuant	2	31.62	0.8887	28.54	0.8038	27.85	0.7679	25.30	0.7685	28.46	0.8814
CondiQuant	2	33.00	0.9130	29.44	0.8253	28.45	0.7882	26.36	0.8080	30.88	0.9203
CompSRT (ours)	2	34.17	0.9248	30.21	0.8401	28.97	0.8017	27.86	0.8456	33.11	0.9414

Table 7: Performance comparison with SOTA methods for scale factor ($\times 3$) across different bit widths. All comparative results are taken from SwinIR-light [Liang et al. \(2021\)](#), PTQ4ViT [Yuan et al. \(2024\)](#), NoisyQuant [Liu et al. \(2023\)](#), 2DQuant [Liu et al. \(2024\)](#), and CondiQuant [Liu et al. \(2025\)](#). Our method achieves superior performance across all datasets and bitwidths.

7.3 LLM USAGE

We used LLMs to assist—but not replace—our research workflow. Specifically, LLMs were employed to (i) help draft and refactor code snippets and experimental scripts, (ii) brainstorm and clarify ideas and concepts discussed in the paper, (iii) suggest edits and critiques on early drafts, and (iv) provide limited writing assistance for grammar and phrasing. All model outputs were reviewed, verified, and, where needed, rewritten by the authors; we independently implemented, tested, and validated every algorithmic choice and experimental result reported. No proprietary, confidential, or unreleased data were provided to the models. LLMs were not used to generate or fabricate data, analyses, or citations, and they are not listed as authors. The authors bear full responsibility for the paper’s content, including the correctness of code, experiments, and references.