

Method

I quantize either in RGB (C=1) or YUV (C=2) and always evaluate quality back in RGB. The error metric follows the assignment: $\text{AbsErr} = \sum |\text{orig} - \text{out}|$ over all pixels & channels. For context I also report MSE and PSNR. A round-trip RGB→YUV→RGB with 8/8/8 yields $\text{MSE} \approx 0$ in my implementation.

Lowest AbsErr settings

For each (N, C, M) I list the lowest-error tuple from my sweep. For N=4, I include the output images; for N=6 and N=8, only numbers are required by the spec. The tables below list the top four configurations by AbsErr (lowest first) for each N. Complete per-tuple results are included at the end. N=4 shows images; N=6/8 show metrics only.

Winners																
#	N	#	C	#	M	#	Q1	#	Q2	#	Q3	AbsErr	#	MSE	PSNR	Out
	8		2		2		4		2		2	3803049		38.895255		32.232
	8		2		2		4		3		1	4324774		51.933606		30.976
	8		2		2		5		2		1	4505464		54.544266		30.763
	8		2		2		4		1		3	4620292		71.365888		29.596
	6		2		2		3		2		1	5949618		91.002986		28.54
	6		2		2		4		1		1	6118439		102.102444		28.04
	6		2		2		3		1		2	6260240		106.124987		27.873
	6		1		2		2		2		2	7665772		140.898376		26.642
	4		2		2		2		1		1	9645316		233.614253		24.446
	4		1		2		1		2		1	12446175		366.224829		22.493
	4		1		2		2		1		1	13357974		463.186328		21.473
	4		1		2		1		1		2	13685675		495.759991		21.178



Discussion of Results

Case 1: C=1, M=1 (RGB + Uniform)

Uniform bins don't adapt to the data, so starving any channel hurts. As the budget grows, balanced splits minimize error: at N=6 the winner is (2,2,2), and at N=8 it's (2,3,3). With the very tight N=4 budget, (1,2,1) edges out the other RGB uniform splits, but the general trend remains: balance helps once you have a few more bits to spread.

Case 2: C=1, M=2 (RGB + Smart)

Data-adaptive quantization consistently improves over uniform at the same N. Balanced allocations remain best: (2,2,2) wins at N=6 and (3,3,2) at N=8, both with clearly lower AbsErr and higher PSNR than uniform. Even at N=4, (1,2,1) leads the RGB smart group.

Case 3: C=2, M=1 (YUV + Uniform)

The best rows bias bits toward Y: (2,1,1) at N=4, (3,2,1) at N=6, and (4,2,2) at N=8. That matches perception—structure and edges are largely luminance—yet uniform chroma bins still waste bits where U/V are sparse, so errors remain higher than smart.

Case 4: C=2, M=2 (YUV + Smart)

Luminance-heavy splits are strongest here too: (2,1,1) at N=4, (3,2,1) at N=6, and (4,2,2) at N=8. With enough total bits, this Y-heavy strategy yields the lowest AbsErr overall (e.g., (4,2,2) at N=8), preserving structure while keeping enough chroma precision to avoid hue shifts.

Overall Conclusion

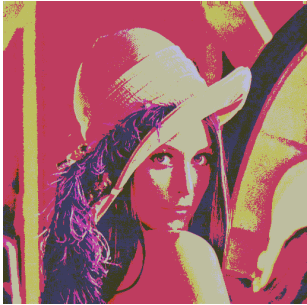
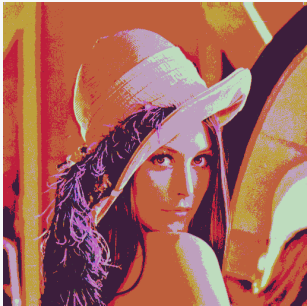
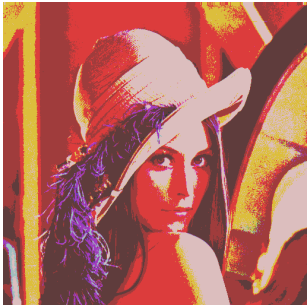
Smart consistently beats uniform at the same N. With very tight budgets, YUV + smart with a Y bias is best by AbsErr. As N increases, YUV + smart with more bits on Y continues to lead on AbsErr (e.g., (3,2,1) at N=6, (4,2,2) at N=8), while RGB + smart (balanced) remains a very strong runner-up and visually neutral. A simple rule that works well: use smart quantization; in YUV, steer extra bits to Y; in RGB, keep bits roughly balanced.


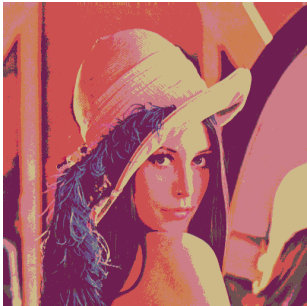

What I'm submitting


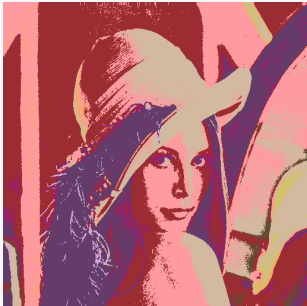
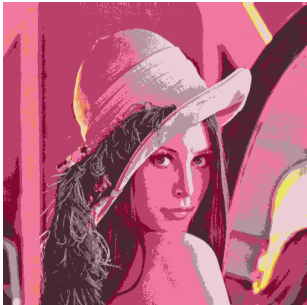
- N=4 table with images and N=6/N=8 tables with error numbers, all directly from analysis.csv (sorted by AbsErr ascending per N).
- This narrative section referencing the lowest-error tuples above.
- Reproducibility: the CSV was generated by my Analysis target; N=4 PNGs are named as shown in the table.
- [Link to spreadsheet with all analysis and images](#)
- [Link to Google doc of this analysis which contains image embeds](#)


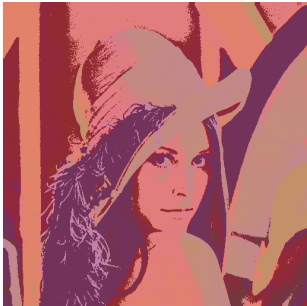
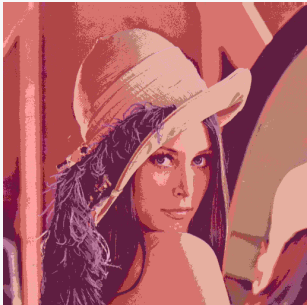
N = 4

N	C	M	Q1	Q2	Q3	AbsErr	MSE	PSNR	Out
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4	1	1	1	1	2	20155030	921.748866	18.485	
4	1	1	1	2	1	19402808	881.191981	18.68	
4	1	1	2	1	1	19664322	964.654627	18.287	

4	1	2	1	1	2	13685675	495.759991	21.178	
4	1	2	1	2	1	12446175	366.224829	22.493	
4	1	2	2	1	1	13357974	463.186328	21.473	

4	2	1	1	1	2	23754460	1357.980021	16.802	
4	2	1	1	2	1	23840711	1199.288174	17.342	
4	2	1	2	1	1	16691323	671.646036	19.859	

4	2	2	1	1	2	18066996	736.881994	19.457	
4	2	2	1	2	1	17639663	709.752603	19.62	
4	2	2	2	1	1	9645316	233.614253	24.446	

N = 6

N	C	M	Q1	Q2	Q3	AbsErr	MSE	PSNR
6	1	1	1	1	4	16705026	800.596624	19.097
6	1	1	1	2	3	13757406	486.573939	21.259
6	1	1	1	3	2	13955956	496.903488	21.168
6	1	1	1	4	1	16210078	771.494553	19.257
6	1	1	2	1	3	14018920	570.036585	20.572
6	1	1	2	2	2	12230628	330.471603	22.939
6	1	1	2	3	1	13465248	539.80925	20.808
6	1	1	3	1	2	14928880	611.456426	20.267
6	1	1	3	2	1	14176658	570.899541	20.565
6	1	1	4	1	1	17275616	887.118963	18.651
6	1	2	1	1	4	12237283	468.906254	21.42
6	1	2	1	2	3	9284685	248.81201	24.172
6	1	2	1	3	2	8658057	221.03749	24.686
6	1	2	1	4	1	10125308	305.025625	23.287
6	1	2	2	1	3	10196484	345.773509	22.743
6	1	2	2	2	2	7665772	140.898376	26.642
6	1	2	2	3	1	8330356	188.463826	25.379
6	1	2	3	1	2	9917898	334.731829	22.884
6	1	2	3	2	1	8678398	205.196668	25.009
6	1	2	4	1	1	11564910	422.638964	21.871
6	2	1	1	1	4	23628916	1326.677485	16.903
6	2	1	1	2	3	23874581	1161.35456	17.481
6	2	1	1	3	2	22531885	1073.382964	17.823
6	2	1	1	4	1	22421624	1074.703369	17.818
6	2	1	2	1	3	14337241	543.46247	20.779
6	2	1	2	2	2	11488631	317.909054	23.108
6	2	1	2	3	1	12599283	372.56831	22.419
6	2	1	3	1	2	11973879	400.309172	22.107
6	2	1	3	2	1	10021168	251.333227	24.128
6	2	1	4	1	1	13612608	455.30556	21.548

6	2	2	1	1	4	18039000	734.496648	19.471
6	2	2	1	2	3	17680564	703.938886	19.655
6	2	2	1	3	2	17621430	697.886215	19.693
6	2	2	1	4	1	17493051	695.883068	19.705
6	2	2	2	1	3	9252776	209.746943	24.914
6	2	2	2	2	2	9002019	188.477103	25.378
6	2	2	2	3	1	9037676	193.578807	25.262
6	2	2	3	1	2	6260240	106.124987	27.873
6	2	2	3	2	1	5949618	91.002986	28.54
6	2	2	4	1	1	6118439	102.102444	28.04

N = 8

N	C	M	Q1	Q2	Q3	AbsErr	MSE	PSNR
8	1	1	1	1	6	15915842	793.908529	19.133
8	1	1	1	2	5	12085312	457.870682	21.523
8	1	1	1	3	4	10505952	375.751246	22.382
8	1	1	1	4	3	10564676	376.876511	22.369
8	1	1	1	5	2	12343920	469.290756	21.416
8	1	1	1	6	1	15422758	764.747564	19.296
8	1	1	2	1	5	12346826	541.333328	20.796
8	1	1	2	2	4	8780624	209.319361	24.923
8	1	1	2	3	3	7819846	145.191208	26.511
8	1	1	2	4	2	9037898	220.774175	24.691
8	1	1	2	5	1	11853212	512.196518	21.036
8	1	1	3	1	4	11478876	490.304184	21.226
8	1	1	3	2	3	8531256	176.281499	25.669
8	1	1	3	3	2	8729806	186.611048	25.421
8	1	1	3	4	1	10983928	461.202113	21.492
8	1	1	4	1	3	11630214	492.500921	21.207
8	1	1	4	2	2	9841922	252.935939	24.101
8	1	1	4	3	1	11076542	462.273585	21.482
8	1	1	5	1	2	13367756	584.508784	20.463

8	1	1	5	2	1	12615534	543.951899	20.775
8	1	1	6	1	1	16445124	879.974508	18.686
8	1	2	1	1	6	11816707	466.117303	21.446
8	1	2	1	2	5	8503397	240.941639	24.312
8	1	2	1	3	4	7209665	194.183753	25.249
8	1	2	1	4	3	6963818	187.612806	25.398
8	1	2	1	5	2	7505214	205.149694	25.01
8	1	2	1	6	1	9521187	300.417645	23.354
8	1	2	2	1	5	9415196	337.903137	22.843
8	1	2	2	2	4	6217380	114.04464	27.56
8	1	2	2	3	3	5168866	71.051008	29.615
8	1	2	2	4	2	5344905	79.699172	29.116
8	1	2	2	5	1	7177513	172.576031	25.761
8	1	2	3	1	4	8469506	307.878092	23.247
8	1	2	3	2	3	5516908	87.783849	28.697
8	1	2	3	3	2	4890280	60.009328	30.349
8	1	2	3	4	1	6357531	143.997463	26.547
8	1	2	4	1	3	8403420	305.226145	23.285
8	1	2	4	2	2	5872708	100.351013	28.116
8	1	2	4	3	1	6537292	147.916463	26.431
8	1	2	5	1	2	9003697	323.500075	23.032
8	1	2	5	2	1	7764197	193.964914	25.254
8	1	2	6	1	1	11046169	419.010985	21.909
8	2	1	1	1	6	23612289	1324.552377	16.91
8	2	1	1	2	5	23871742	1156.891833	17.498
8	2	1	1	3	4	22380588	1040.34152	17.959
8	2	1	1	4	3	22393745	1030.146114	18.002
8	2	1	1	5	2	22523220	1054.301727	17.901
8	2	1	1	6	1	22377156	1067.134201	17.849
8	2	1	2	1	5	14197367	535.740103	20.841
8	2	1	2	2	4	10972506	285.099584	23.581
8	2	1	2	3	3	10459317	254.665844	24.071
8	2	1	2	4	2	10541198	259.554688	23.989

8	2	1	2	5	1	12146590	344.823285	22.755
8	2	1	3	1	4	10980143	364.797586	22.51
8	2	1	3	2	3	7263170	136.807755	26.77
8	2	1	3	3	2	7180684	124.986186	27.162
8	2	1	3	4	1	8622341	193.388872	25.266
8	2	1	4	1	3	9778850	330.093984	22.944
8	2	1	4	2	2	6815764	119.013583	27.375
8	2	1	4	3	1	8121934	165.699028	25.938
8	2	1	5	1	2	10830412	347.096865	22.726
8	2	1	5	2	1	8807864	193.927625	25.254
8	2	1	6	1	1	13454729	440.349072	21.693
8	2	2	1	1	6	18024165	732.926177	19.48
8	2	2	1	2	5	17668144	702.501007	19.664
8	2	2	1	3	4	17591383	694.860124	19.712
8	2	2	1	4	3	17551754	692.305023	19.728
8	2	2	1	5	2	17571381	693.573243	19.72
8	2	2	1	6	1	17484002	695.085869	19.71
8	2	2	2	1	5	9205150	207.399437	24.963
8	2	2	2	2	4	8832952	178.468877	25.615
8	2	2	2	3	3	8628687	169.335954	25.843
8	2	2	2	4	2	8686945	173.66177	25.734
8	2	2	2	5	1	8951477	188.992596	25.366
8	2	2	3	1	4	5873936	96.430478	28.289
8	2	2	3	2	3	4880907	60.266689	30.33
8	2	2	3	3	2	4847146	57.83239	30.509
8	2	2	3	4	1	5500209	78.046678	29.207
8	2	2	4	1	3	4620292	71.365888	29.596
8	2	2	4	2	2	3803049	38.895255	32.232
8	2	2	4	3	1	4324774	51.933606	30.976
8	2	2	5	1	2	4671411	70.257348	29.664
8	2	2	5	2	1	4505464	54.544266	30.763
8	2	2	6	1	1	5793527	92.093876	28.488