Dog Image Grooming Salon

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Digital Image Processing
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01

Big Problem

Big Problem

In today's digital world, dog photos are some of the most commonly shared—seen on social media, pet websites, and custom products. But getting clear, good-looking dog pictures is not easy. We need smart image editing tools to fix lighting, improve sharpness, and make the dog stand out from the background.

In this project, we explore three image improvement methods separately: contrast enhancement to fix lighting, noise reduction to make images clearer, and background blurring to keep the focus on the dog. These methods help turn everyday dog photos into high-quality images with little manual work.

02

Dataset

Dataset

Dataset	#Image	#Objects	In which experiment was used	Year
Stanford Dogs Dataset[1]	15	1	1,3	2011
Tsinghua Dogs Dataset[2]	10	1	2	2020
Exclusively-Dark-Image-Dataset[3]	5	1	1	2015

[1] “Stanford Dogs Dataset,” *Kaggle*, Nov. 13, 2019. https://www.kaggle.com/datasets/jessicali9530/stanford-dogs-dataset/data?select=images

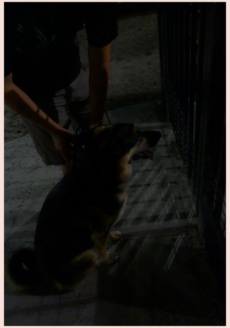
[3] Zou, Ding-Nan, et al. “A New Dataset of Dog Breed Images and a Benchmark for Finegrained Classification.” Computational Visual Media, vol. 6, no. 4, Oct. 2020, pp. 477–87. https://doi.org/10.1007/s41095-020-0184-6.

[3] Loh, Yuen Peng, and Chee Seng Chan. “Getting to Know Low-light Images With the Exclusively Dark Dataset.” Computer Vision and Image Understanding, vol. 178, Nov. 2018, pp. 30–42. https://doi.org/10.1016/j.cviu.2018.10.010.

Dataset-exp1


D0


D1


D2


D3


D4

5 Dark-Lighting Images (Exclusively-Dark-Image-Dataset)


L0


L1


L2


L3


L4

5 Excess-Lighting Images (Stanford Dogs Dataset)

Dataset-exp2


C0


C1

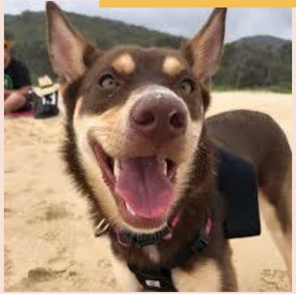

C2


C3


C4

10 Low-Resolution Images (Tsinghua Dogs Dataset)


C5


C6


C7


C8


C9

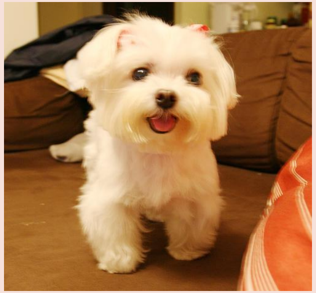
Dataset-exp3


E0


E1

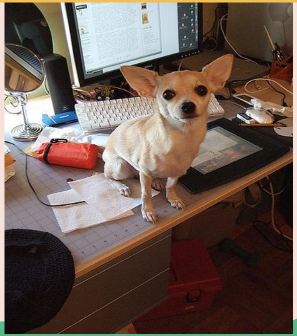

E2


E3


E4

5 Low-Clutter Backgrounds Images (Stanford Dogs Dataset)


H0


H1


H2


H3

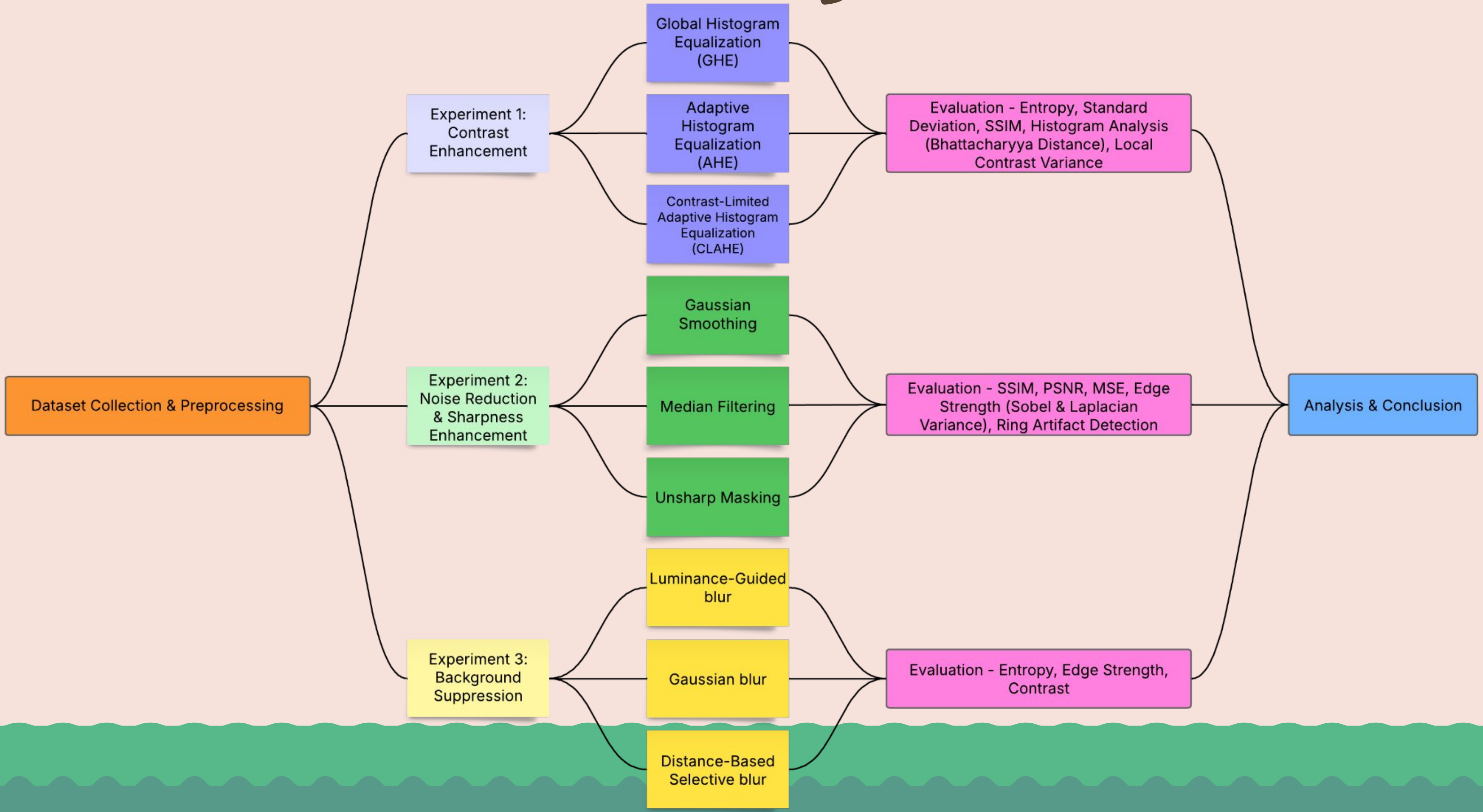

H4

5 High-Clutter Background Images (Stanford Dogs Dataset)

03

Experiment Design

Block Diagram



Experiment 1: Localized Contrast Enhancement

01 **GHE**
Global Histogram Equalization

02 **AHE**
Adaptive Histogram Equalization

03 **CLAHE**
Contrast-Limited Adaptive Histogram Equalization

Method	Parameter	Test Range
GHE	Num of Histogram Bins (n)	{32, 64, 128, 256}
AHE	Tile Size (NumTiles)	{8×8, 16×16, 32×32}
CLAHE	Tile Size (NumTiles)	{8×8, 16×16, 32×32}
	Clip Limit (ClipLimit)	{2, 4, 6, 8}

Metrics	Indication
Entropy	Higher values -> better contrast enhancement
StdDev	Higher values -> better contrast enhancement
SSIM	Higher values -> better contrast enhancement
LCV	Higher values -> better contrast enhancement
Bhatt Distance	Lower values -> better contrast enhancement

Apply normalization to metrics, scaling all values between 0 and 1:
- Norm_Metric1 = (Metric−Min(Metric))/(Max(Metric)−Min(Metric)), if higher values is better
- Norm_Metric2 = 1−(Metric−Min(Metric))/(Max(Metric)−Min(Metric)), if lower values is better

Final Metrics Scores:
- Score = (0.25 × Norm_Entropy) + (0.25 × Norm_StdDev) + (0.20 × Norm_SSIM) + (0.15 × Norm_Bhattacharyya) + (0.15 × Norm_LCV)

Choose Best Parameter for Each image in each method:
- Parameter with Higher Score -> Better Contrast Enhancement

Compare Methods Performance:
- Average 5 Dark-Lighting images' score
- Average 5 Excess-Lighting images' score
- Average all 10 images' score

Experiment 2: Edge-Preserving Noise Reduction and Sharpness Enhancement

01 Gaussian Smoothing

02 Median Filtering

03 Unsharp Masking

Method	Parameter	Test Range
Gaussian Smoothing	Sigma (σ)	{0.4, 0.6, 0.8, 1.0}
Median Filtering	Window Size (w*w)	{3*3, 5*5, 7*7}
Unsharp Masking	Unsharp Amount (n)	{0.5, 1.0, 1.5, 2.0}

Metrics	Indication
SSIM	Higher values -> better overall quality and edge preservation
PSNR	Higher values -> better noise reduction
MSE	Lower values -> better noise reduction
Sobel	Higher values -> better edge sharpness
Ring	Lower values -> better visual quality and artifact suppression

Final Metrics Scores:

- Score = (0.4 × SSIM) + (0.3 × PSNR) - (0.1 × MSE) + (0.1 × Sobel) + (0.1 × LaplacianVar) - (0.1 × Ring)

Choose Best Parameter for Each image in each method:

- Parameter with Higher Score -> Better Contrast Enhancement

Compare Methods Performance:

- Average all 10 images’ score

Experiment 3: Automated Background Suppression

01 Luminance blur

02 Gaussian blur

03 Distance-Based Selective blur

Method	Parameter	Test Range
Luminance blur	Gaussian Sigma (σ)	{5, 10, 15, 20}
Gaussian blur	Gaussian Sigma (σ)	{5, 10, 15, 20}
Distance-Based Selective blur	Multi-level Sigma (σ)	{[5,10,20,30,50], [10,20,30,40,60], [15,30,50,70,90], [20,40,60,80,100]}

Metrics	Indication
Entropy	Lower values -> better background suppression
Edge Strength	Higher values -> better background suppression
Contrast	Higher values -> better background suppression

Apply normalization to metrics, scaling all values between 0 and 1:

- Norm_Metric = (Metric−Min(Metric))/(Max(Metric)−Min(Metric))

Final Metrics Scores:

- Score = 0.3 * (1 - Norm_Entropy/8) +0.4 * Norm_EdegeStrength + 0.3 * Norm_Contrast

Choose Best Parameter for Each image in each method:

- Parameter with Higher Score -> Better Contrast Enhancement

Compare Methods Performance:

- Average 5 Low-Clutter Background images' score
- Average 5 High-Clutter Background images' score
- Average all 10 images' score

04

Experiment Results

Experiment 1: Localized Contrast Enhancement - Quantitative Results

01 GHE
Global Histogram Equalization

02 AHE
Adaptive Histogram Equalization

03 CLAHE
Contrast-Limited Adaptive Histogram Equalization

Image	Method	Bins	Entropy	StdDev	SSIM	Bhattacharyya	LCV
D0	GHE	0	5.3219	0.0640	1.0000	0.0000	0.0002
D0	GHE	32	4.5750	0.2975	0.1847	0.9197	0.0190
D0	GHE	64	4.8714	0.2930	0.1915	0.9186	0.0183
D0	GHE	128	5.0750	0.2906	0.1940	0.9198	0.0180
D0	GHE	256	5.2359	0.2895	0.1951	0.9228	0.0179
L0	GHE	0	6.3987	0.1152	1.0000	0.0000	0.0006
L0	GHE	32	4.8709	0.2975	0.5064	0.9011	0.0035
L0	GHE	64	5.6232	0.2927	0.5242	0.8750	0.0033
L0	GHE	128	6.2100	0.2903	0.5332	0.8500	0.0032
L0	GHE	256	6.3464	0.2898	0.5366	0.8436	0.0032

Image	Method	Bins	Score
D0	GHE	256	0.4497
D1	GHE	256	0.5472
D2	GHE	256	0.3352
D3	GHE	256	0.4847
D4	GHE	128	0.5310
L0	GHE	256	0.5576
L1	GHE	256	0.7195
L2	GHE	256	0.5874
L3	GHE	256	0.5755
L4	GHE	256	0.7429
10 Images Average Score			0.5531

	GHE	AHE	CLAHE
5 Dark-Lighting Images Avg Score	0.4696	0.3646	0.5220
5 Excess-Lighting Images Avg Score	0.6366	0.7267	0.7264
10 Images Avg Score	0.5531	0.5457	0.6242

Experiment 1: Localized Contrast Enhancement - Qualitative Results

Original of D0

GHE of D0

Original of L0

GHE of L0

AHE of D0

CLAHE of D0

AHE of L0

CLAHE of L0

Experiment 2: Edge-Preserving Noise Reduction and Sharpness Enhancement - Quantitative Results

01 Gaussian Smoothing

02 Median Filtering

03 Unsharp Masking

Image	Method	Sigma	SSIM	PSNR	MSE	Sobel	LaplacianVar	Ring
C3	Gaussian Smoothing	0.40	0.9987	48.5775	0.0000	0.0337	0.0058	0.0734
C3	Gaussian Smoothing	0.60	0.9794	36.8419	0.0002	0.0299	0.0024	0.0438
C3	Gaussian Smoothing	0.80	0.9541	33.5427	0.0004	0.0265	0.0013	0.0291
C3	Gaussian Smoothing	1.00	0.9315	31.8963	0.0006	0.0233	0.0009	0.0213
C4	Gaussian Smoothing	0.40	0.9965	42.8852	0.0000	0.0261	0.0216	0.1323
C4	Gaussian Smoothing	0.60	0.9463	31.5068	0.0007	0.0244	0.0090	0.0703
C4	Gaussian Smoothing	0.80	0.8913	28.5854	0.0014	0.0227	0.0060	0.0440
C4	Gaussian Smoothing	1.00	0.8513	27.2441	0.0019	0.0214	0.0050	0.0317

Image	Method	Sigma	Score
C0	Gaussian Smoothing	0.4	12.7210
C1	Gaussian Smoothing	0.4	13.9944
C2	Gaussian Smoothing	0.4	14.5704
C3	Gaussian Smoothing	0.4	14.9694
C4	Gaussian Smoothing	0.4	13.2557
C5	Gaussian Smoothing	0.4	13.6687
C6	Gaussian Smoothing	0.4	14.8520
C7	Gaussian Smoothing	0.4	12.6805
C8	Gaussian Smoothing	0.4	15.7508
C9	Gaussian Smoothing	0.4	14.1552
10 Images Avg Score			14.0618

	Gaussian Smoothing	Median Filtering	Unsharp Masking
10 Low-Resolution Images Avg Score	14.0618	9.3413	10.9634

Experiment 2: Edge-Preserving Noise Reduction and Sharpness Enhancement - Qualitative Results

Original of C3

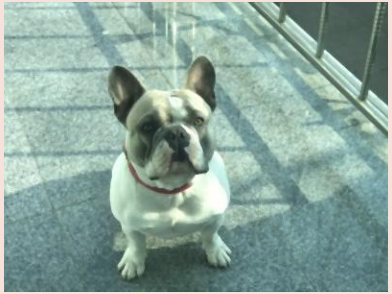
Gaussian Smoothing of C3

Original of C4

Gaussian Smoothing of C4

Median Filtering of C3

Unsharp Masking of C3



Median Filtering of C4

Unsharp Masking of C4

Experiment 3: Automated Background Suppression - Quantitative Results

01 Luminance blur

02 Gaussian blur

03 Distance-Based Selective blur

Image	Method	Luminance Sigma	Entropy	EdgeStrength	Contrast
E0	Luminance blur	5	5.6516	0.0320	1.5718
E0	Luminance blur	10	5.6516	0.0320	1.5718
E0	Luminance blur	15	5.6516	0.0320	1.5718
E0	Luminance blur	20	5.6516	0.0320	1.5718
H0	Luminance blur	5	6.7314	0.0179	1.6034
H0	Luminance blur	10	6.7314	0.0179	1.6034
H0	Luminance blur	15	6.7314	0.0179	1.6034
H0	Luminance blur	20	6.7314	0.0179	1.6034

Image	Method	Luminance Sigma	Score
E0	Luminance blur	5	0.5724
E1	Luminance blur	5	0.4258
E2	Luminance blur	5	0.4491
E3	Luminance blur	5	0.4173
E4	Luminance blur	5	0.3106
H0	Luminance blur	5	0.5357
H1	Luminance blur	5	0.5674
H2	Luminance blur	5	0.4074
H3	Luminance blur	5	0.5007
H4	Luminance blur	5	0.3112
10 Images Average Score			0.4498

	Luminance blur	Gaussian blur	Selective blur
5 Low-Clutter Images Avg Score	0.4350	0.5534	0.6383
5 High-Clutter Images Avg Score	0.4645	0.5971	0.7223
10 Images Avg Score	0.4498	0.5752	0.6803

Experiment 3: Automated Background Suppression - Qualitative Results

Original of E0

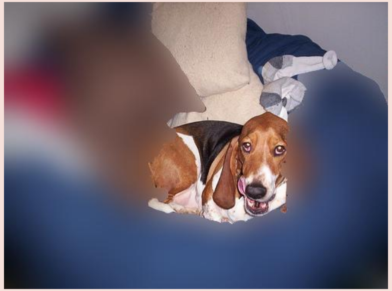
Luminance blur of E0

Original of H0

Luminance blur of H0

Gaussian blur of E0

Selective blur of E0



Gaussian blur of H0

Selective blur of H0

05

Conclusion

Conclusion

Experiment 1: Contrast Enhancement

- CLAHE gave the best results when tile size and clip limit were carefully tuned. ✅
- GHE improved overall visibility but lacked flexibility for uneven lighting.
- AHE worked well locally but struggled with very dark images.

Experiment 2: Noise Reduction and Sharpness

- Gaussian Smoothing balanced noise reduction and edge clarity best. ✅
- Unsharp Masking enhanced sharpness but risked adding artifacts.
- Median Filtering preserved edges but was less effective overall.

Experiment 3: Background Suppression

- Distance-Based Selective Blur provided the clearest subject isolation. ✅
- Gaussian Blur was effective but less precise than selective methods.
- Luminance Blur had minimal impact on complex scenes.

Future Work & Challenge

Future Work

Pipeline integration:
Combine contrast, sharpness, and background steps into a single end-to-end enhancement tool.

Deep learning integration:
Explore machine learning and deep learning methods for automated background suppression and enhancement.

Challenge

Parameter Selection:
Tuning parameters manually was time-consuming and required trial-and-error for each image.

Dog Segmentation:
Separating dogs from background was difficult without using object detection or segmentation models.

Thanks!

Do you have any questions?

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