Aligning Subjective and Objective Assessments in Super-Resolution Models

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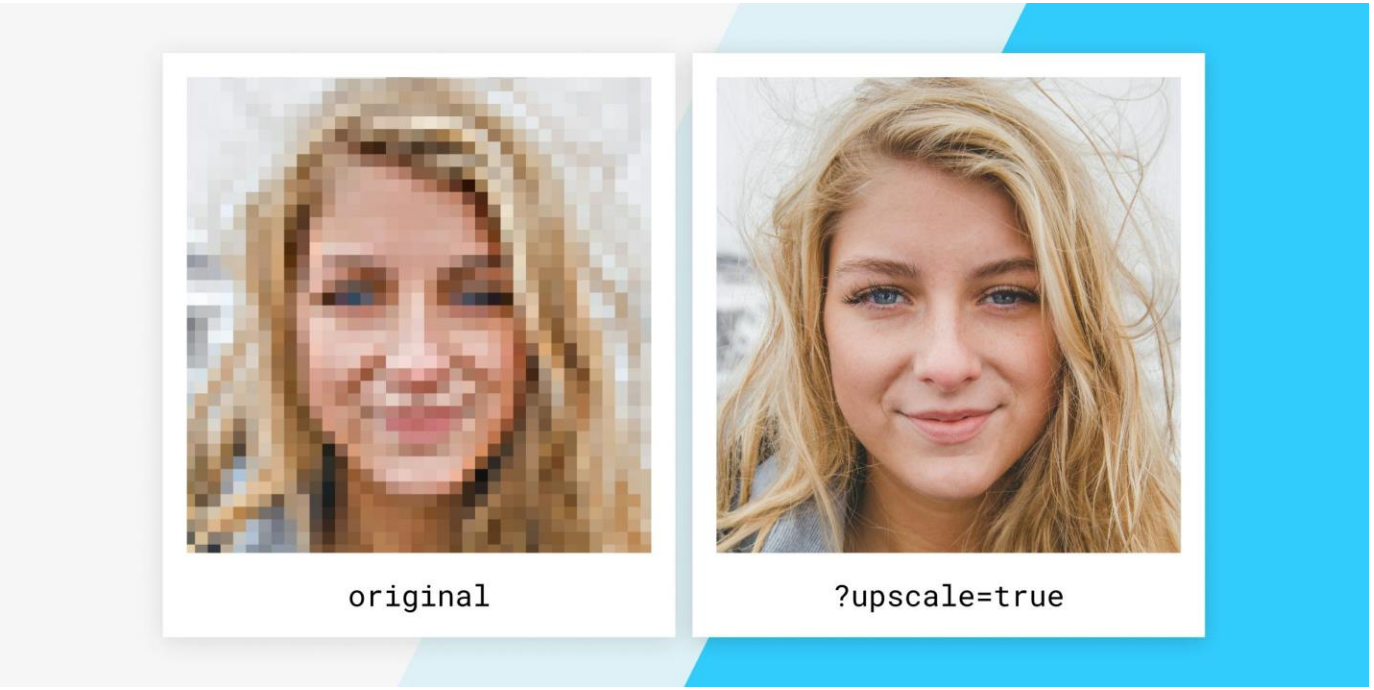
Introduction



- Super-resolution (SR) enhances image details
- Objective metrics dominate (e.g., PSNR, SSIM)
- Need: Incorporate human perceptual assessments

Ref: https://www.imgix.com/blog/ai-powered-image-super-resolution

Motivation

- Why evaluate SR models beyond PSNR/SSIM?
- Problem: Objective metrics ≠ Human perception
- Visual: A high-PSNR image with poor perceptual quality
- Despite high **PSNR of 27.92** and **SSIM of 0.940**, the reconstructed image (center) appears **lacks perceptual sharpness**.
- **LPIPS = 0.047** also indicates high perceptual similarity
- Traditional metrics like PSNR and SSIM can be misleading when evaluating perceptual quality in super-resolution.

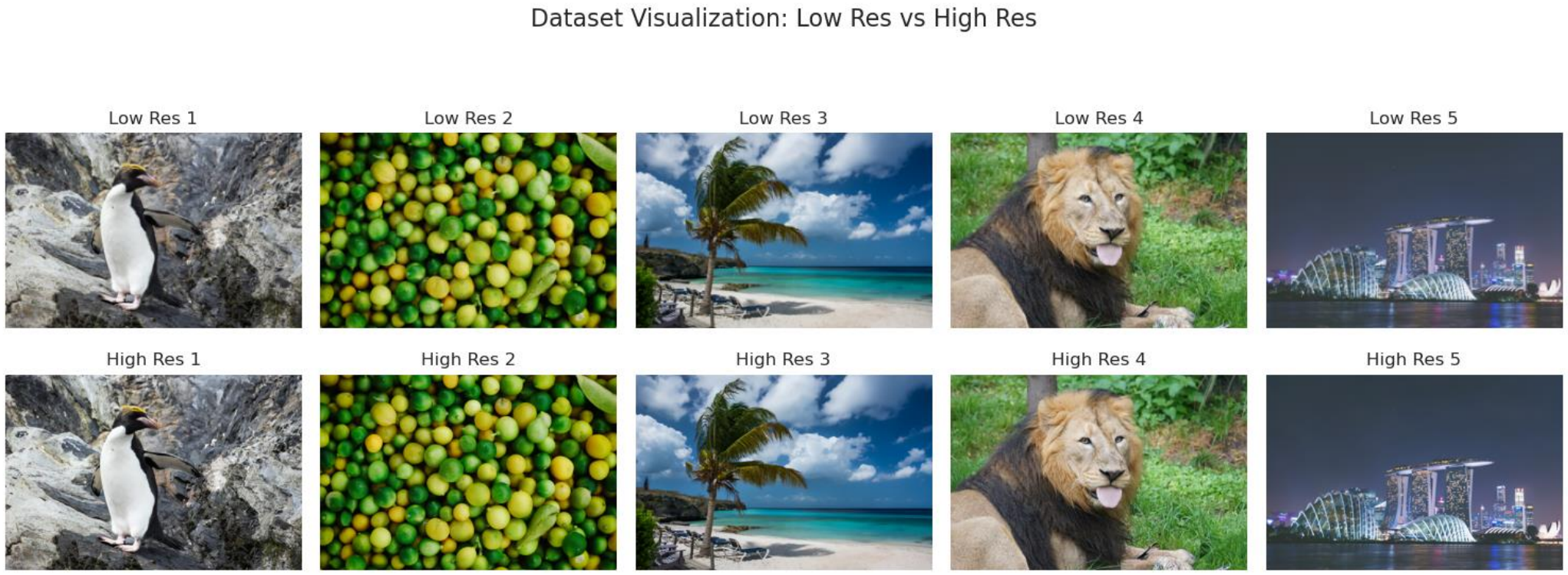
Evaluated Models

- 4 SR models:
  - **ResShift, Real-ESRGAN, BSRGAN, SwinIR**
- Some models report only a subset of objective metrics, which can mislead comparisons.
  - For example, BSRGAN omits SSIM, while ResShift includes LPIPS, SSIM, PSNR, and even CLIPIQA.
  - Fair evaluation requires consistent reporting across metrics.
- **ResShift** (Diffusion-based) - Claims SOTA
- **Critical Missing Piece**
  - **No subjective evaluation** for these models
  - **Limited understanding** of human preferences
  - **Objective-subjective alignment** unclear

Model	Year	Architecture	Objective Metrics	Subjective Assessment
ResShift	2023	Diffusion-based	PSNR, SSIM, LPIPS, CLIPIQA, MUSIQ	*None*
Real-ESRGAN	2021	GAN-based	PSNR, SSIM, LPIPS	*None*
BSRGAN	2021	GAN-based	PSNR, LPIPS	*None*
SwinIR	2021	Transformer-based	PSNR, SSIM, LPIPS	*None*

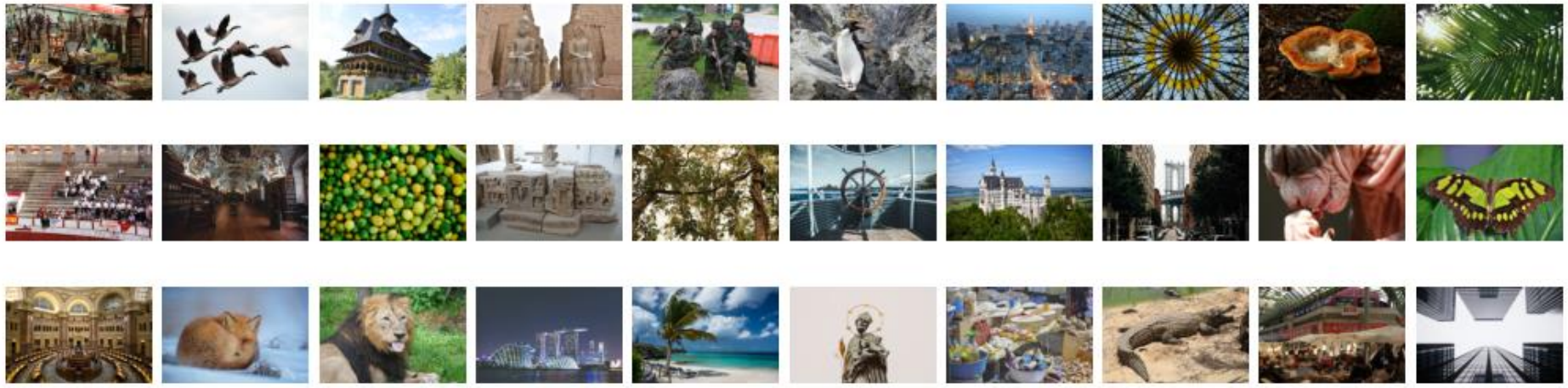
Dataset: DIV2K

- Standard benchmark used in super-resolution challenges
- High-quality, diverse 2K resolution images across various content types
- Low-resolution and high-resolution image pairs created using bicubic x8 and x2 downscaling
- Resolution details:
  - Low-resolution (LR): 255 × 169
  - High-resolution (HR): 1020 × 676 (4× upsampled)



Setup

- No additional preprocessing.
- Setup follows official benchmark protocol
- Used in both objective and subjective evaluations:
  - 30 images for the online single-choice study
  - 10 images for the controlled lab pairwise comparison
    - Subset of the above 30 images.

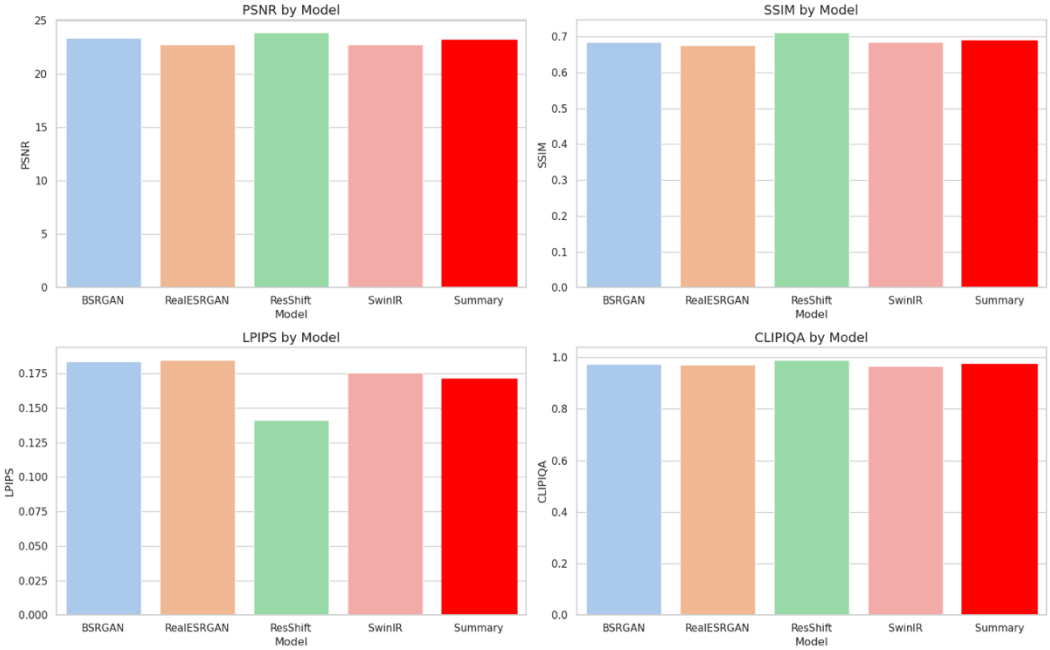


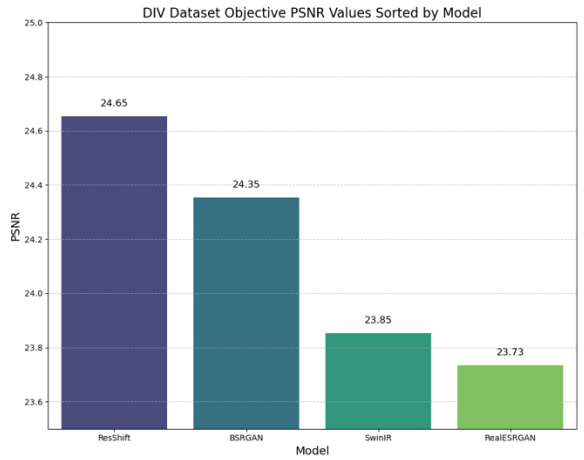
30 images for the online single-choice study

10 images for the controlled lab pairwise comparison

Objective Evaluation

- Metrics: PSNR, SSIM, LPIPS, CLIPIQA on 30 DIV2K Images
- **ResShift leads in 4/4 metrics**
- **BSRGAN shows strong pixel-level performance** with second-highest PSNR
- **RealESRGAN underperforms** across most metrics despite being widely used
- **SwinIR surprisingly lags** in this comparison

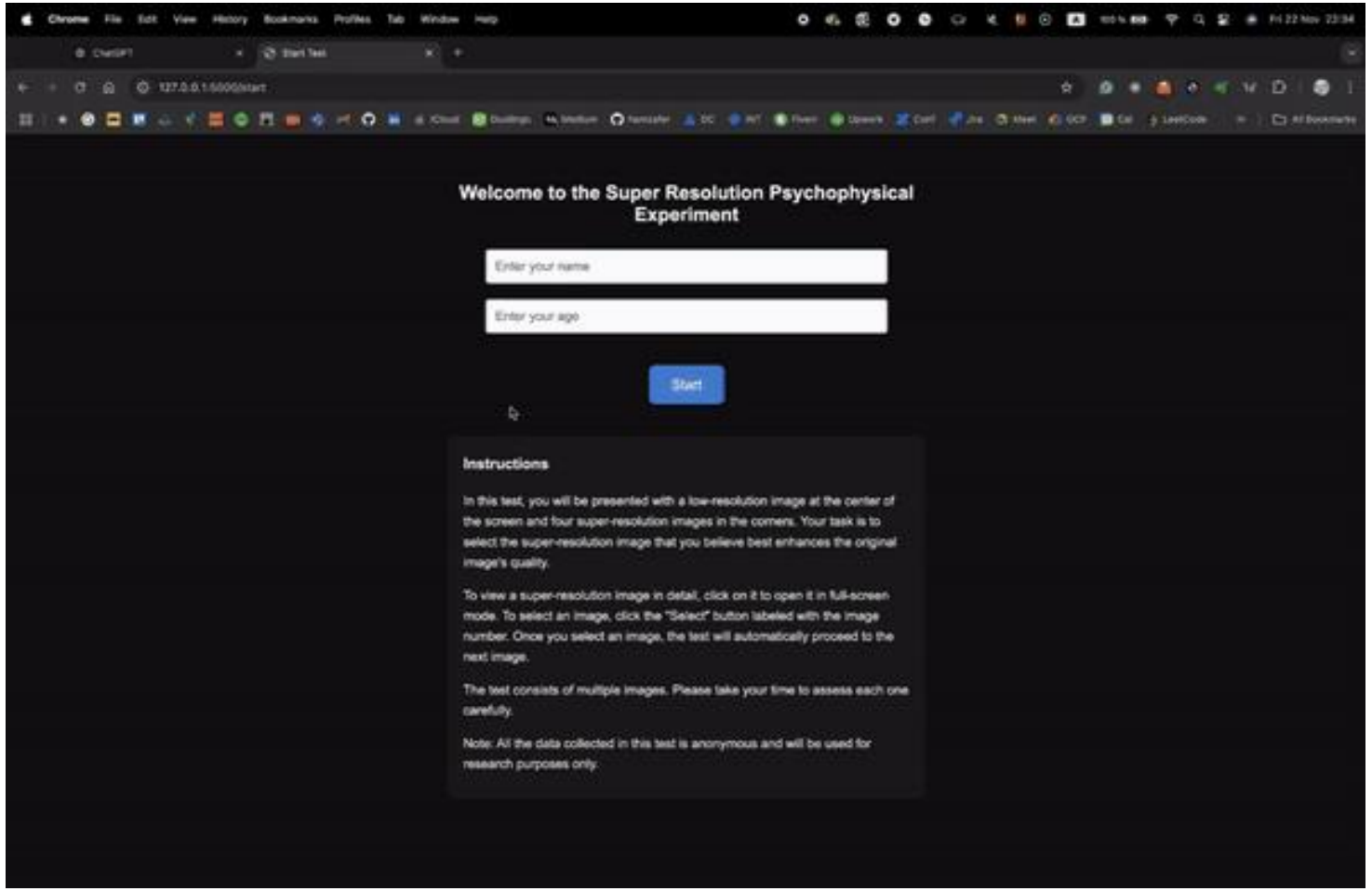




Performance Metrics (DIV2K)

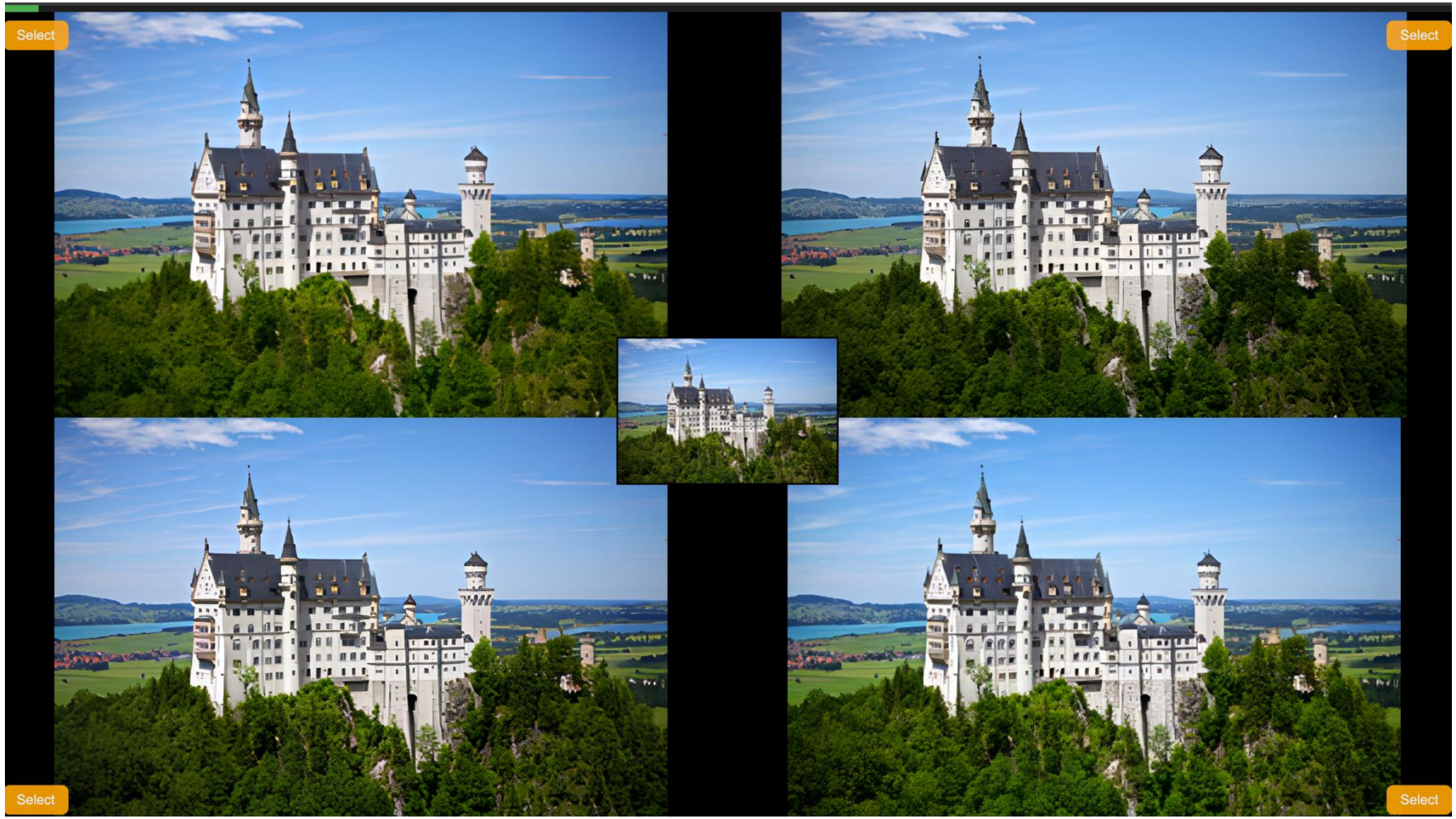
Model	PSNR ↑	SSIM ↑	LPIPS ↓	CLIPIQA ↑
ResShift	**24.65**	**0.723**	**0.136**	**0.986**
BSRGAN	24.35	0.703	0.172	0.977
SwinIR	23.85	0.705	0.164	0.968
Real-ESRGAN	23.73	0.697	0.169	0.972

Experiment 1 – Online Setup



- **Total Images**: 30
- **Estimated Time**: 15 minutes
- **Low-Resolution Image**:
  - Size: 255×169 pixels
  - Position: Center of the screen
- **High-Resolution Images**:
  - Quantity: 4
  - Size: 1020×676 pixels each
  - Display: Surrounding the low-resolution image
- Choose the best HR image from randomized comparisons.

EXPERIMENT 1
SETUP



Experiment 1 – Results

- **Subjective Results:**
  - **What Humans Actually Prefer**
- 134 participants
- 54 completed
- ResShift dominant
  - ResShift: 624 selections ⭐
  - SwinIR: 377 selections
  - Real-ESRGAN: 351 selections
  - BSRGAN: 268 selections

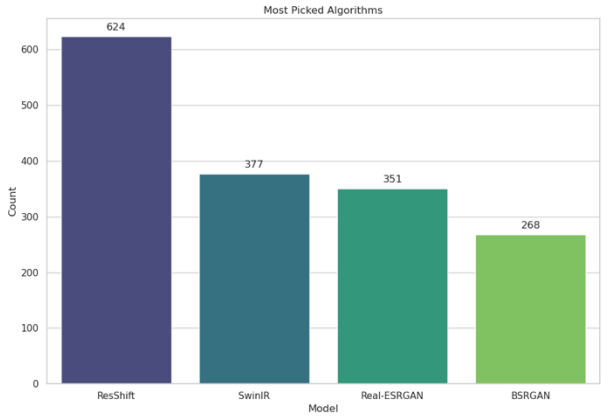
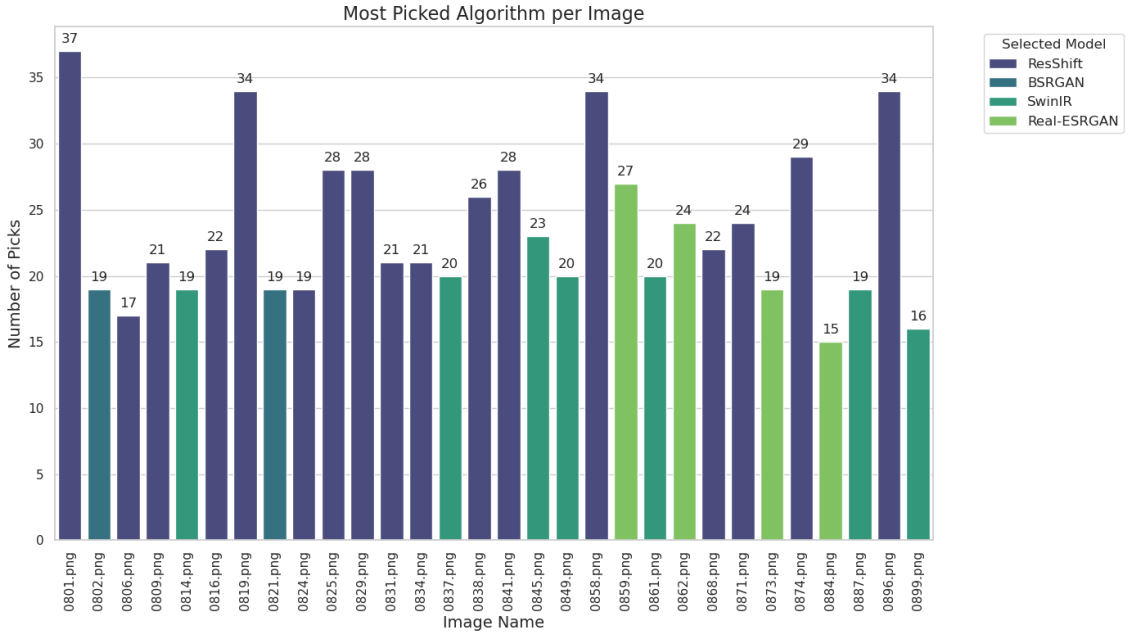


Table 3: Model Preference Results.

Model	Count
ResShift	624
SwinIR	377
Real-ESRGAN	351
BSRGAN	268



Experiment 1 – Results

Image 1: Age Distribution (18-50)

- **Participant demographics**: Heavily skewed toward younger adults
- **Peak at 24-25 years**: 29 and 16 participants respectively (majority of sample)
- **Limited older representation**: Only 3 participants over 35, which could be a limitation

Image 2: Age vs. Algorithm Preference (Age < 30)

- **ResShift dominance**: Consistently highest preference across ALL age groups from 18-28
- **Interesting insight**: ResShift is not the highest picked among 19 & 21 year old
- **SwinIR as second choice**: Generally second-most preferred across age groups

Image 3: Word Cloud - Reasons for Selection

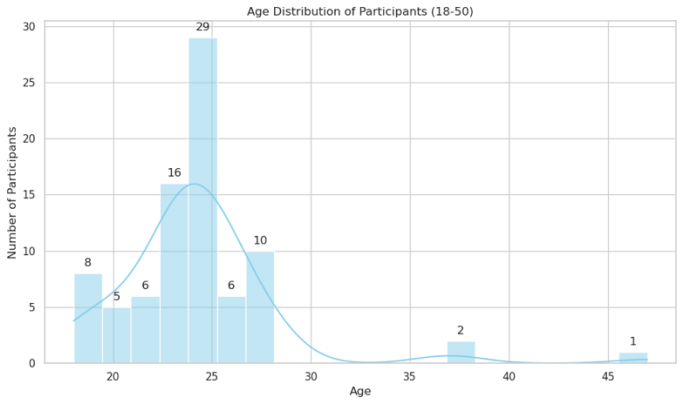
- **Most prominent terms (by size):**
- **"detail"** - Largest term, indicates primary selection criterion
- **"artifact"** - Second largest, shows participants actively avoided visual artifacts

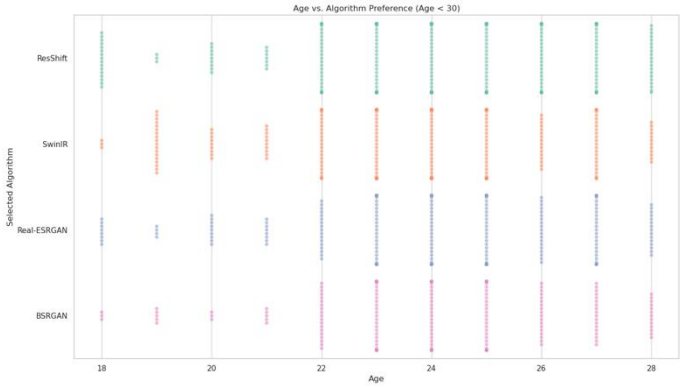
Image 4: Word Cloud - General Feedback

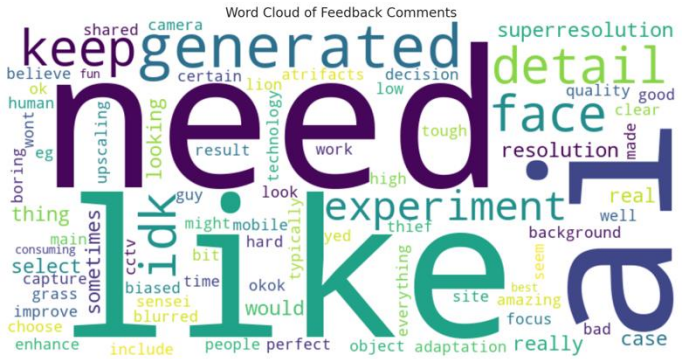
- **"generated"**, **"detail"** - Focus on output quality
- **"quality"**, **"resolution"** - Technical assessment terms

Overall Analysis:

- **Consistent preferences**: ResShift dominance holds across all demographics
- **Quality-focused selection**: Participants prioritized detail preservation and artifact avoidance

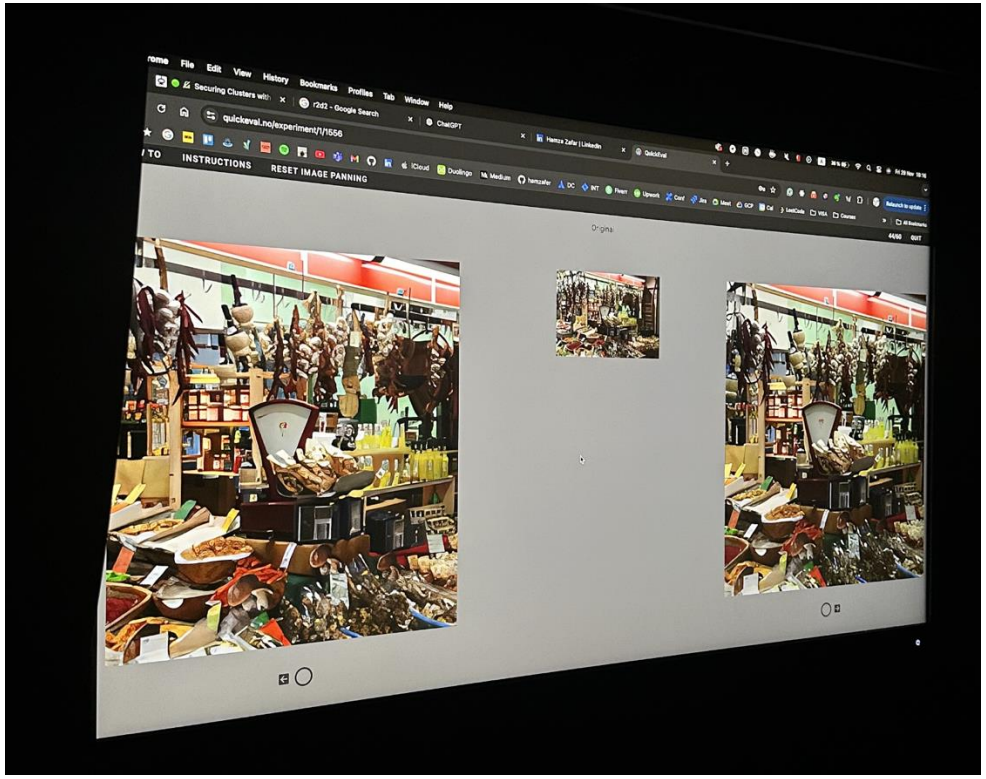


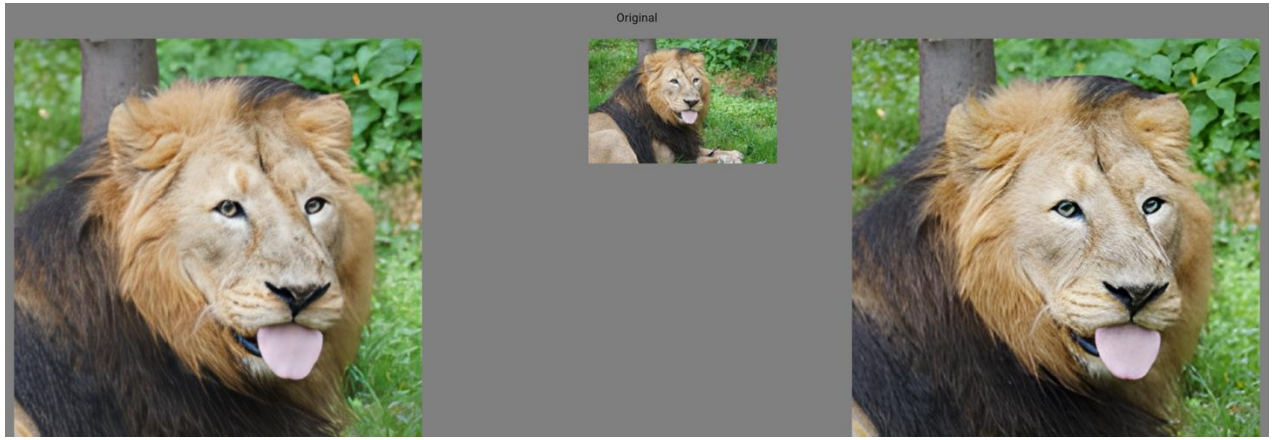




Experiment 2 – Lab Study

- Pairwise comparisons, 10 images, 60 pairs per person
- BenQ calibrated monitor, sRGB, D65, 80 cd/m^2
- Estimated Time: 15 minutes





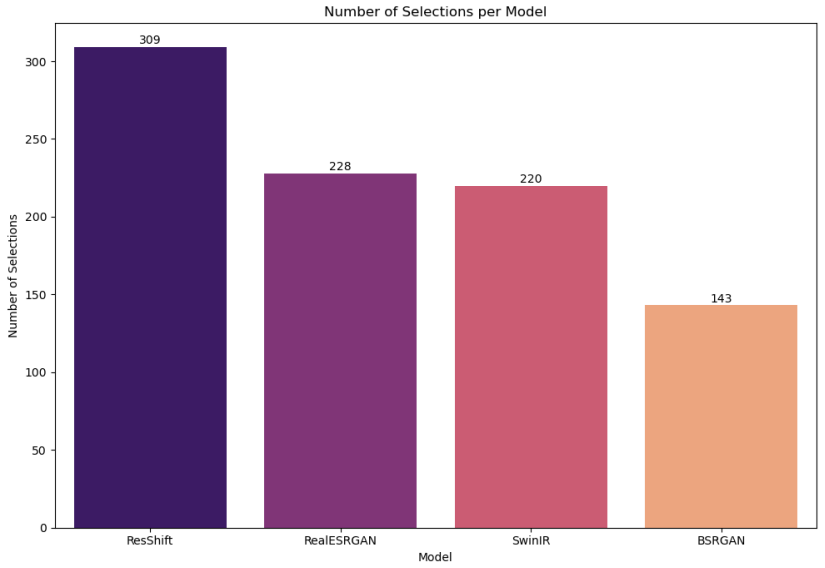
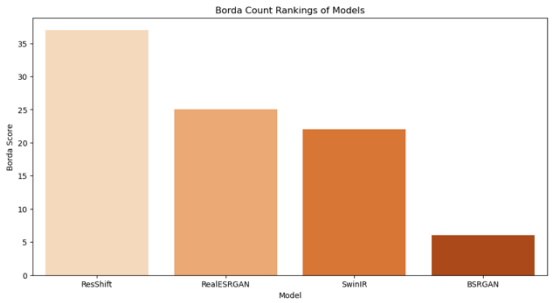


Table 4: Model selections during Experiment 2.

Model	Selections
ResShift	309
RealESRGAN	228
SwinIR	220
BSRGAN	143



Experiment 2 – Results

- 900 pairwise votes, 15 observers
- ResShift dominant again
- Chi-square test ($p < 0.0001$) Results are not due to random chance
- **Bradley-Terry Scores**: ResShift 1.170 (highest ability to be preferred)
- Multiple statistical methods confirm ResShift's superiority

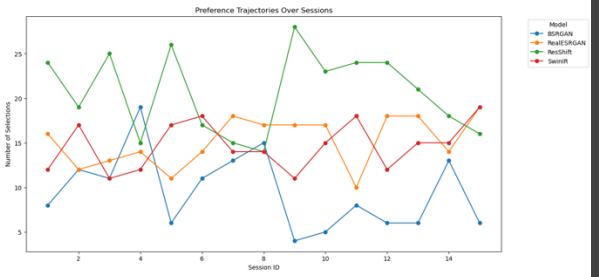
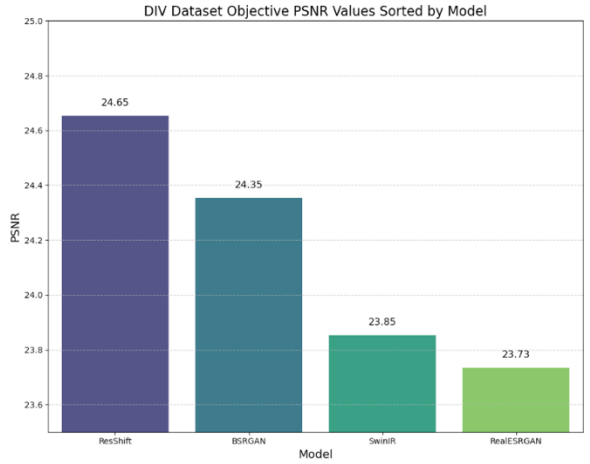


Table 5: Ability estimates for SR models using Bradley-Terry and Thurstone methods.

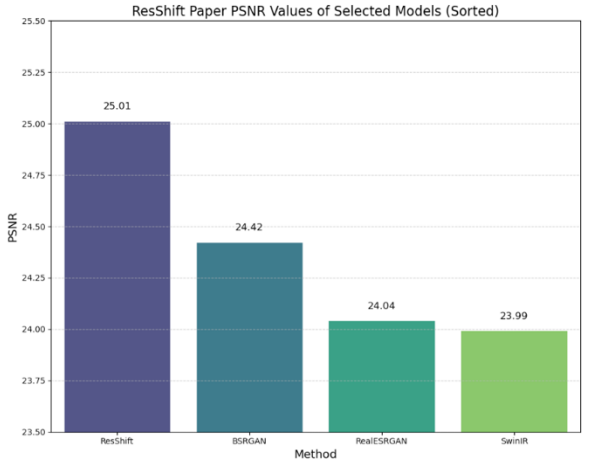
Model	Bradley-Terry Score	Thurstone Score
ResShift	1.170	0.596
RealESRGAN	2.546	0.023
SwinIR	-1.996	-0.036
BSRGAN	-1.720	-0.583

Unified Comparison

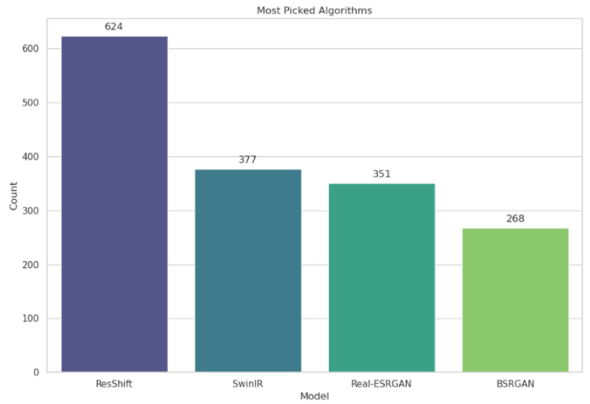
- **ResShift claims validated**: Both objective metrics AND human preferences confirm SOTA status
- **Cross-study consistency**: Online (54 participants) and lab (15 observers) show identical model rankings
- BSRGAN:
  - **Objective-subjective disconnect**: 2nd best PSNR but worst human preference
- **Traditional metrics misleading**: High PSNR ≠ Visual quality



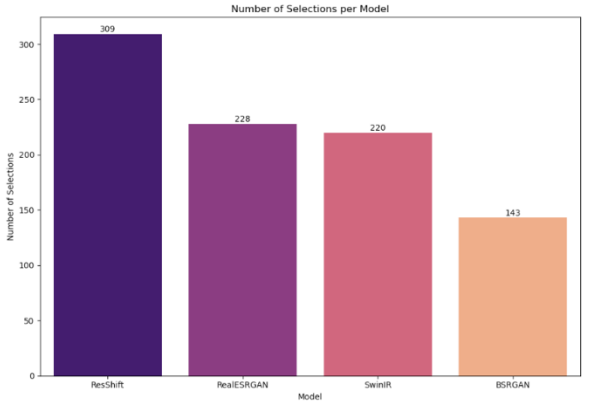
(a) Objective Metrics Results on DIV Dataset.



(b) Objective Metrics Results from Paper.



(c) Experiment 1 Results.



(d) Experiment 2 Results.

Key Insights & Discussion

- Objective ≠ Perceptual always
- ResShift = technically & perceptually strong
- BSRGAN = objectively good, subjectively bad
- Hybrid evaluation is necessary for real-world quality
- **Both studies show identical model rankings**, validating the robustness of human preferences for ResShift's superior perceptual quality.
- The numbers above bars show selections from Exp1 (top) and Exp2 (bottom).

Limitations

- Only 4 models, DIV2K only
- No novel metric proposed
- Small lab (Exp 2) dataset (10 images)
- Still, robust reproducible framework

Conclusion & Future Work

- ResShift sets a new standard in perceptual SR
- Need larger and more diverse datasets
- Explore joint metric-subjective learning for SR
- Push toward **human-centric model evaluation**

Thank You

- Repo: https://github.com/hamzafer/super-resolution-color
- muhamhz@ntnu.no
- https://www.linkedin.com/in/ihamzafer/
- Open for questions ☺

Project Page

Contact

References
1.ResShift: Efficient Diffusion Model for Image Super-resolution by Residual Shifting
Authors: Zongsheng Yue, Jianyi Wang, Chen Change Loy
URL: https://github.com/zsyOAOA/ResShift
2.Real-ESRGAN: Real-Enhanced Super-Resolution Generative Adversarial Networks
Authors: Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Chen Change Loy
URL: https://github.com/xinntao/Real-ESRGAN
3.BSRGAN: Blind Super-Resolution Generative Adversarial Networks
Authors: Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Chen Change Loy
URL: https://github.com/cszn/BSRGAN
4.SwinIR: Image Restoration Using Swin Transformer
Authors: Jingyun Liang, Yiming Ma, Chengjie Wang, Bineng Zhong, Dong Wang
URL: https://github.com/JingyunLiang/SwinIR
5.Agustsson, E., & Timofte, R. (2017). *NTIRE 2017 Challenge on Single Image Super-Resolution: Dataset and Study*. In CVPR Workshops.