

Super Resolution In Video Games



A Survey of Methods



Presented by Gabriel Ribeiro Gomes
Introduction to Deep Learning - Prof. Paulo Ivson
DI - Departamento de Informática @ PUC-Rio
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Summary



1. **Introduction:** What is Super Resolution? 🤔
2. **Related Work:** DLSS and FidelityFX 🔎
3. **Proposed Technique:** SRCNN and HAT models 🔧
4. **Experiments and Results** 💥
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What is Super Resolution? 🤔

Super Resolution (SR) enhances image or video resolution, making visuals clearer and more detailed.

- Uses algorithms to generate high-res images from low-res inputs.
- Key uses:
 - **Medical Imaging:** Better diagnostic images.
 - **Satellite Imagery:** Sharper analysis.
 - **Video Games:** Upscaled graphics without extra asset costs.

Why Does SR Matter in Games? 🎮

Modern games demand high-quality visuals, but high-res assets are costly and resource-intensive.

- SR enables real-time upscaling from lower resolutions, saving resources while maintaining visual quality.
- Benefits:
 - **Performance:** Less hardware strain.
 - **Accessibility:** Playable on lower-end devices.
 - **Cost Efficiency:** Fewer high-res assets needed.

DLSS and FidelityFX



DLSS (Deep Learning Super Sampling) and FidelityFX are leading SR technologies in gaming.

- **DLSS:** Developed by NVIDIA, uses AI to upscale images in real-time, enhancing performance without sacrificing quality.
- **FidelityFX:** AMD's solution, focuses on high-quality upscaling and image enhancement, compatible with a wide range of hardware.
- Both technologies leverage deep learning to improve image quality and performance in games.

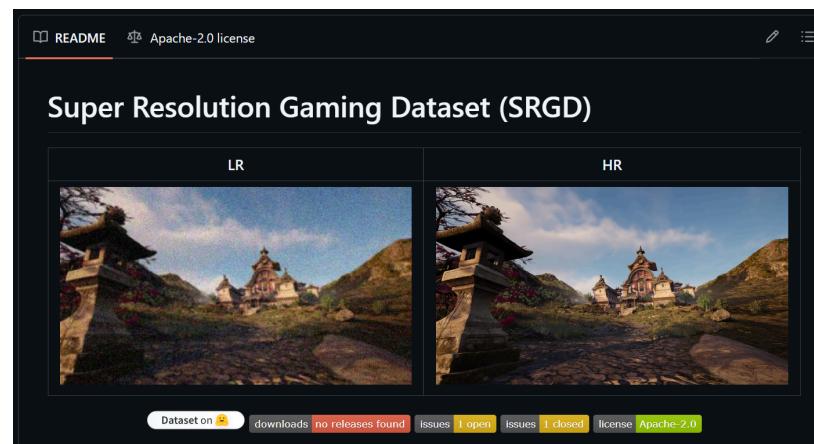
Open Source Alternatives

While DLSS is locked to NVIDIA hardware, more accessible alternatives are emerging. FidelityFX is open source and has a development SDK available.

- Also, there's room for new open-source solutions in the SR space, especially for video games.
- Open source SR solutions can democratize access to high-quality upscaling, allowing developers to implement advanced techniques without proprietary constraints.

Proposed Approach 🔧

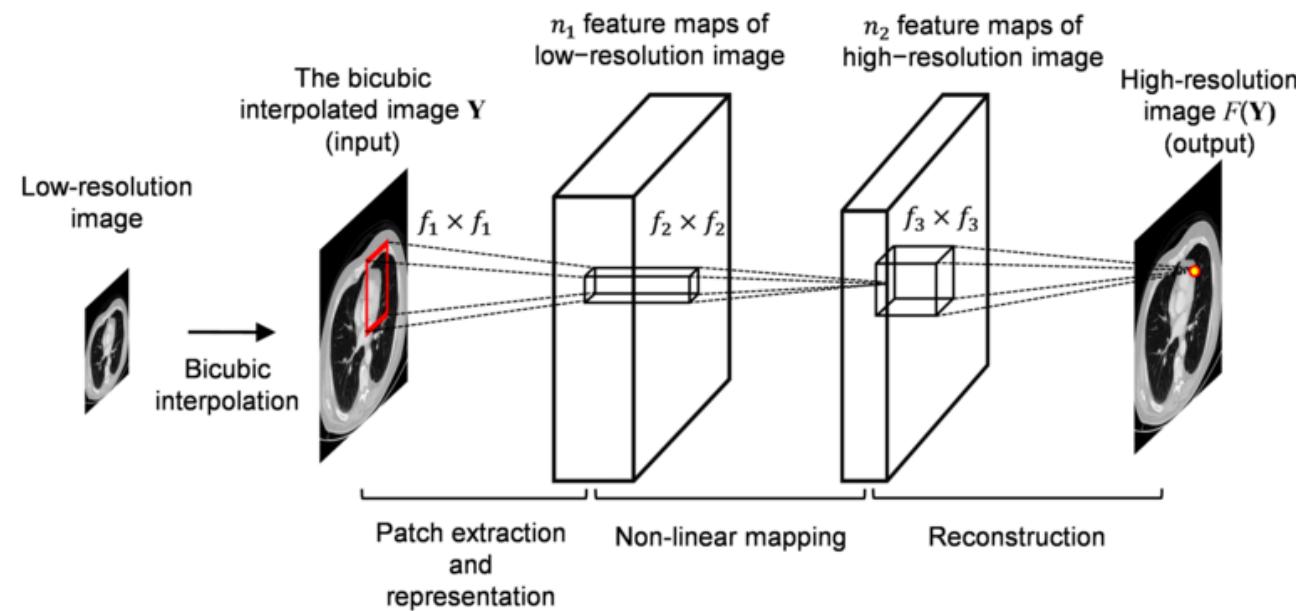
- Use the SRGD as a benchmark for training and testing.
- Implement and evaluate the performance of two models not previously applied to SRGD:
 - **SRCNN** (Super-Resolution Convolutional Neural Network)
 - **HAT** (High-Performance Attention Transformer)



SRCNN

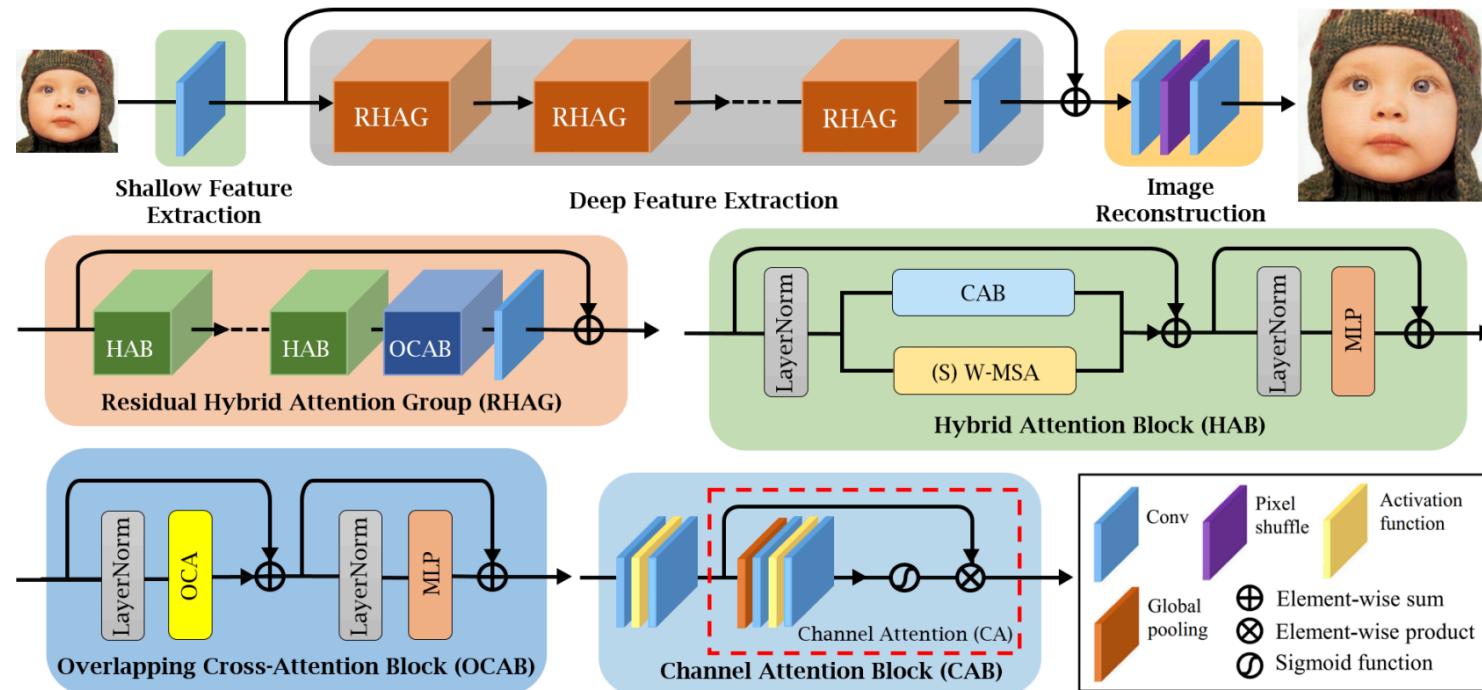


“ SRCNN is one of the first deep learning models for SR, using a simple CNN architecture to reconstruct high-res images from interpolated low-res inputs. ”



HAT

“ HAT uses a hybrid attention transformer architecture, enabling superior perceptual reconstruction at higher computational cost. ”



Experiments and Results



For evaluating the performance of the models, we used the following metrics:

- **PSNR (Peak Signal-to-Noise Ratio)**: Measures the quality of the reconstructed image compared to the original.
- **SSIM (Structural Similarity Index)**: Assesses the structural similarity between the original and reconstructed images.
- **LPIPS (Learned Perceptual Image Patch Similarity)**: Evaluates perceptual similarity, focusing on how humans perceive differences in images.

Machine Setup



Setup Config	Value
OS	Linux 6.1.123+
Processor	x86_64
Python Version	3.11.13
Pytorch Version	2.6.0+cu124
GPU	Tesla T4
GPU Memory	16GB

Results - Quality



Model	PSNR	SSIM	LPIPS	SRGD
SRCNN	24.972	0.746	0.311	This Work
SRCNN-Sharpened	24.476	0.741	0.283	This Work
Real-ESRGAN	23.540	0.799	0.392	Yes
EMT	24.544	0.823	0.388	Yes
ResShift	23.036	0.799	0.482	Yes
HAT	24.743	0.754	0.274	This Work

Results - Inference

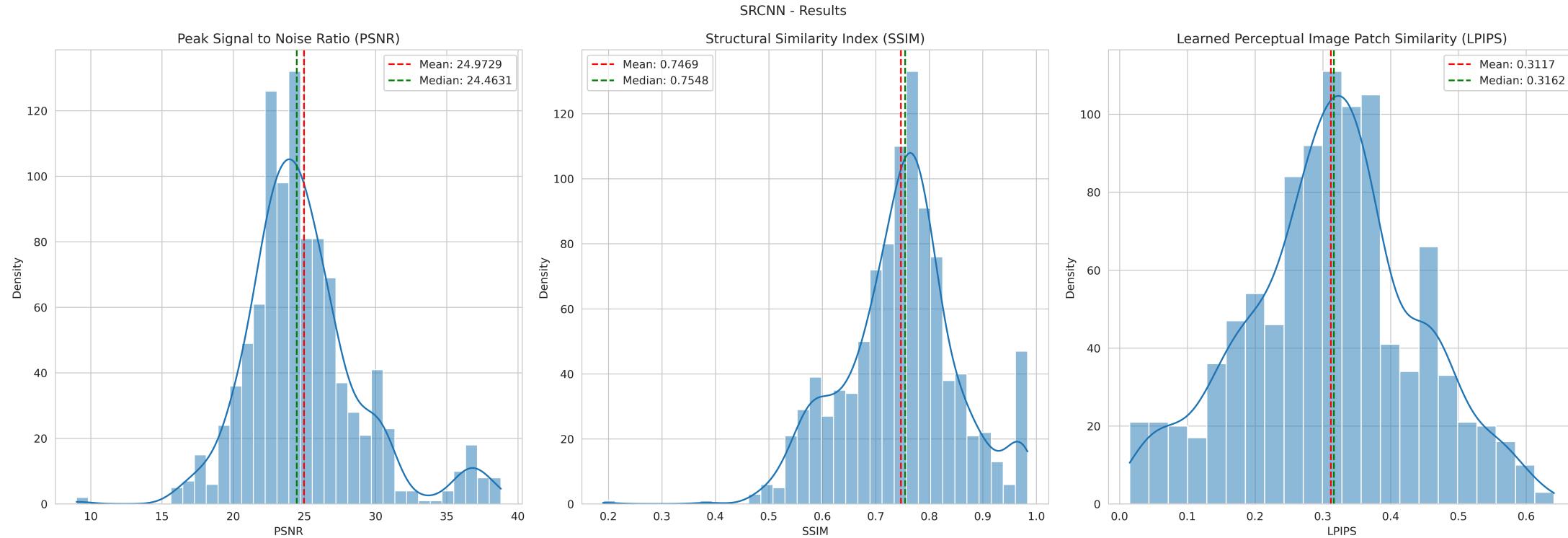


We also got results for the inference time (IT) of the models, which is important for real-time applications like video games.

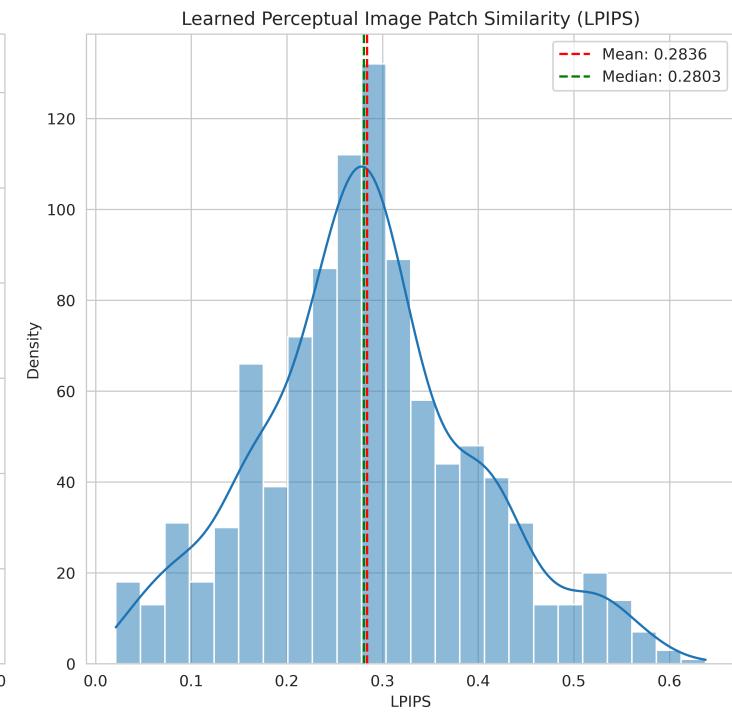
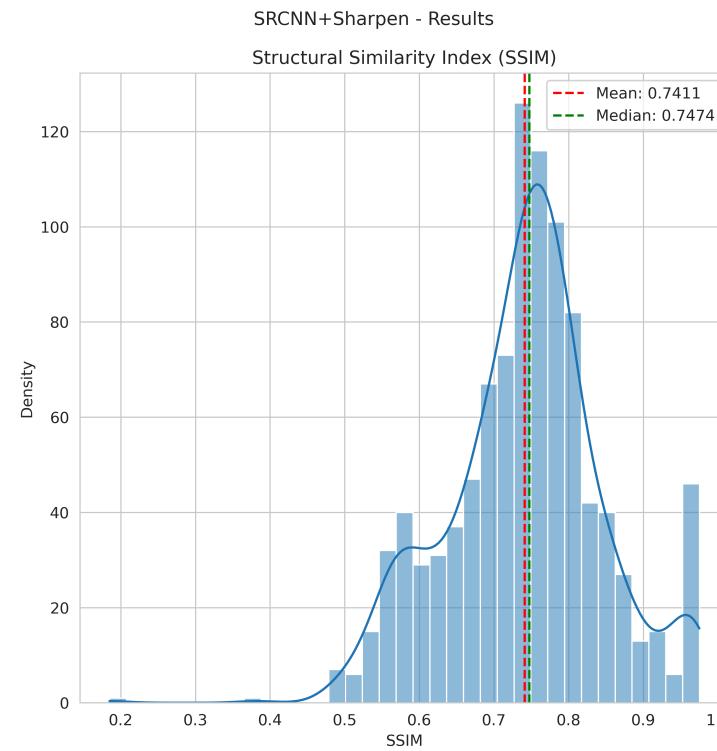
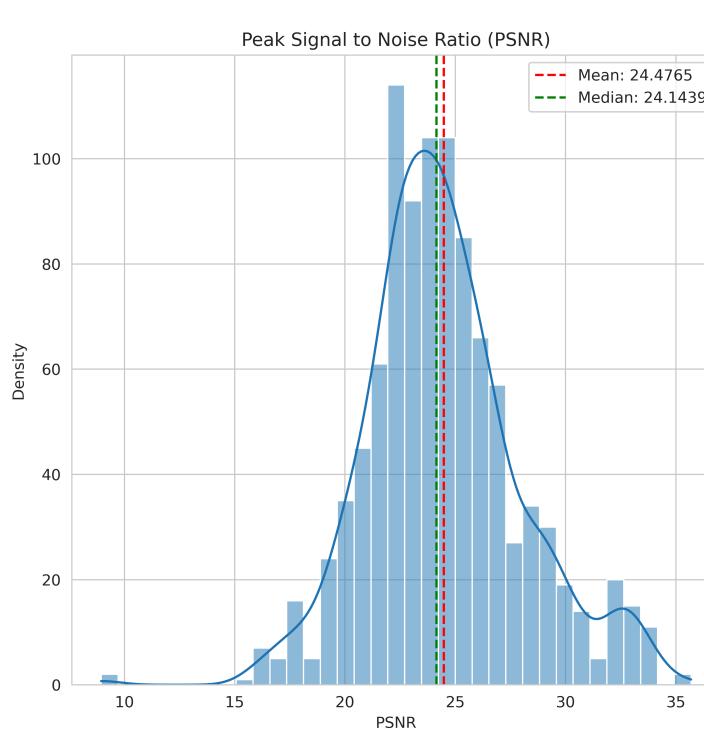
Model	Mean IT (s)	SD IT (s)
SRCNN	0.00109332	0.01748104
HAT	2.27468708	0.07842106

The HAT model is much slower than SRCNN due to its complexity, which can limit its use in real-time scenarios where speed is crucial.

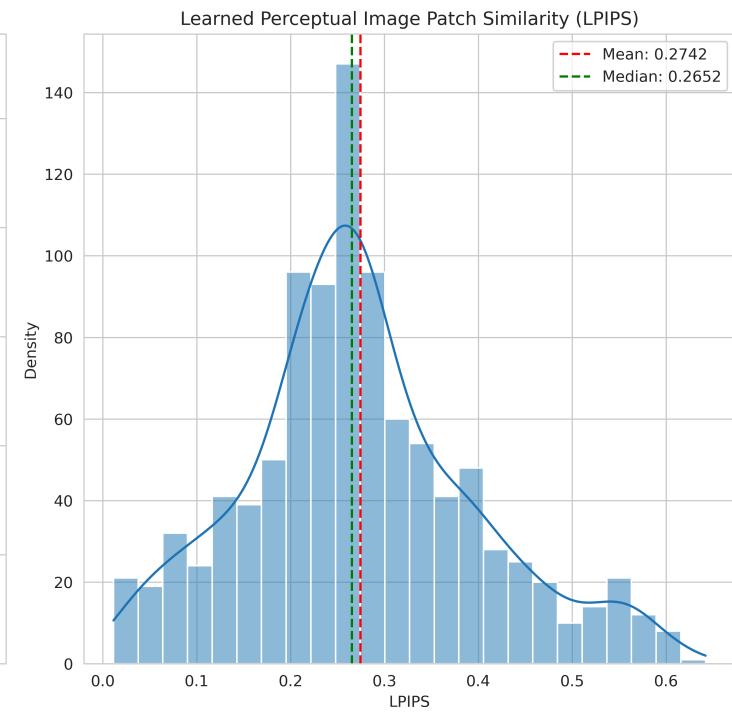
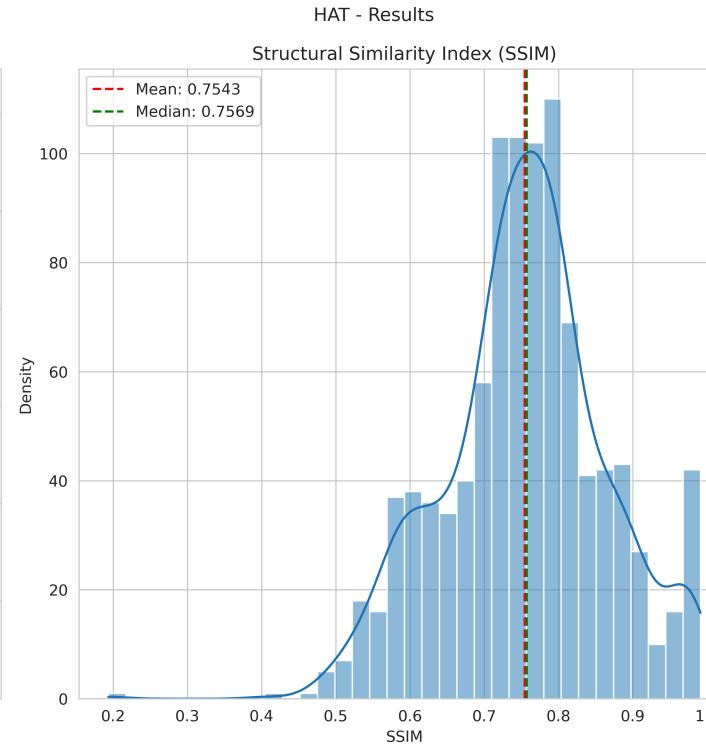
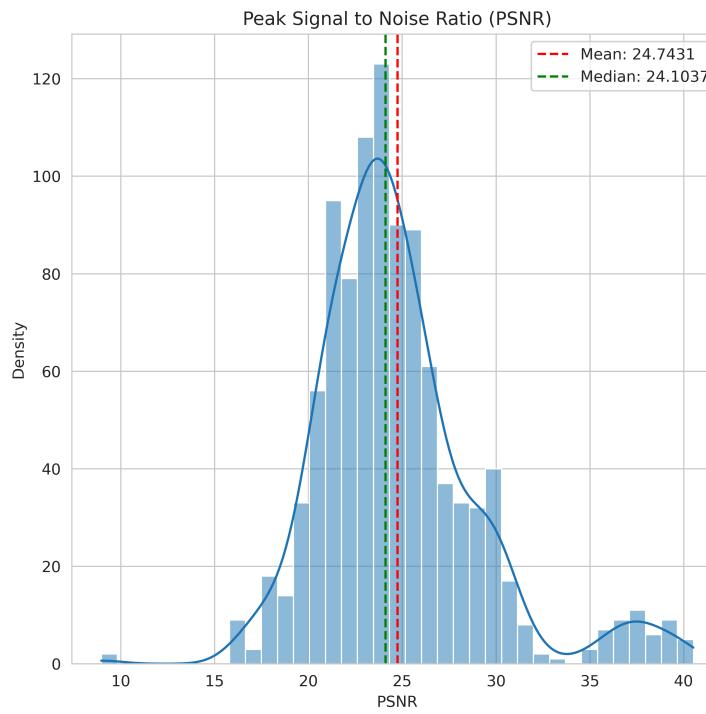
Error Distribution - SRCNN



Error Distribution - Sharpened



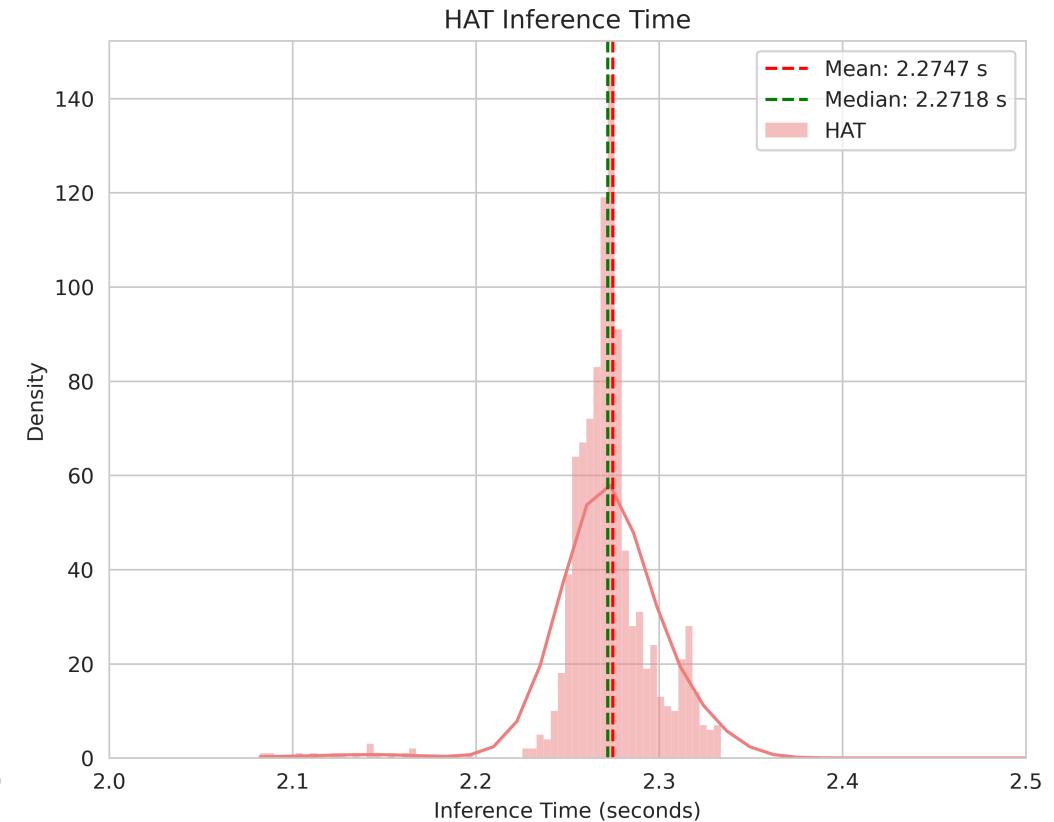
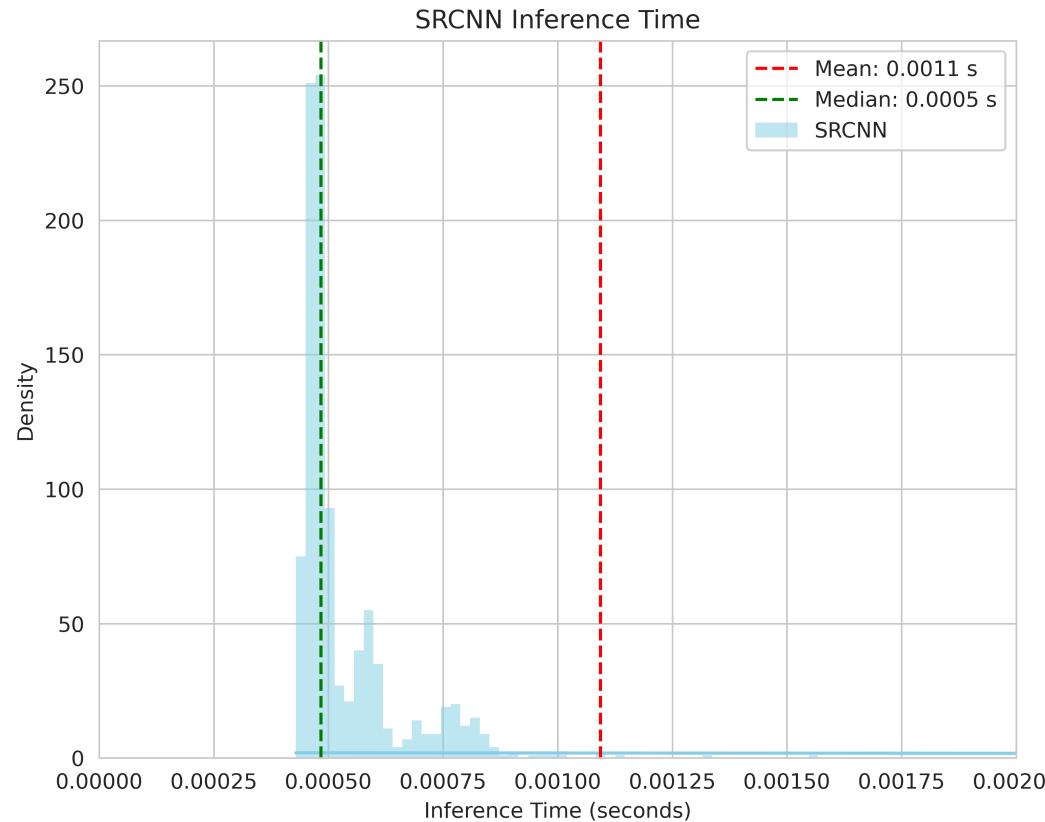
Error Distribution - HAT



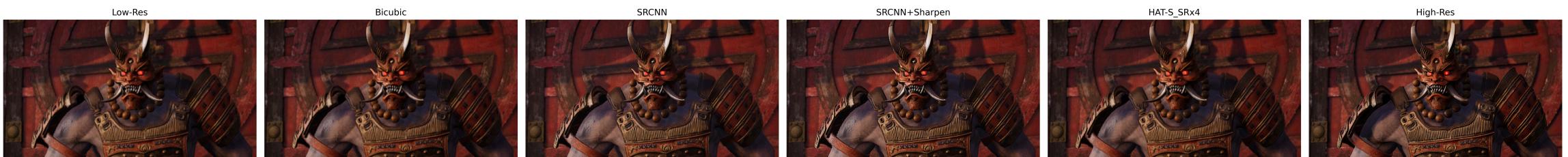
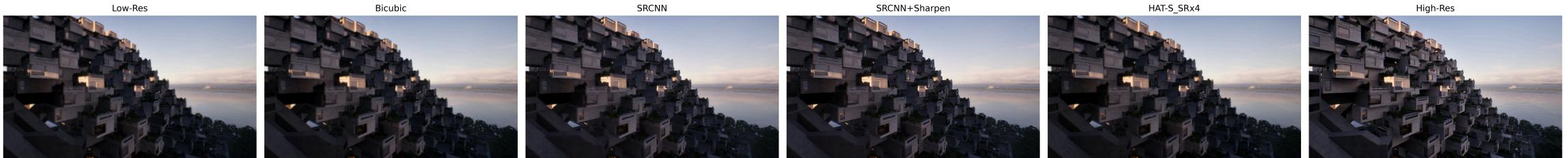
Distribution of Inference Times



Inference Time Distribution - SRCNN and HAT



Experiments and Results



Conclusions and Future Work



- We got a better PSNR on SRCNN models and a better LPIPS on the HAT model, but we still need to improve the SSIM metric.
- Overall, the HAT model shows superior performance in perceptual quality and structural integrity compared to SRCNN.
- We added new information to the SRGD, with the SRCNN (+ Sharpen) and HAT models, which can be used in future works.
- Training more time/epochs with more data and different hyperparameters could improve the results even further.
- Engineering was a bottleneck in this work, since computer vision requires intense CPU/GPU and RAM usage, and datasets are large (50GB+).

Questions?

