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 📚

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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.

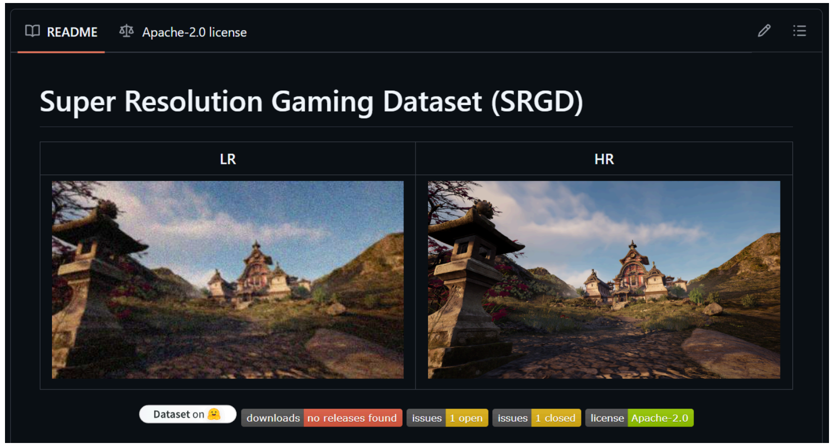
Open Source Alternatives 🔓

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.

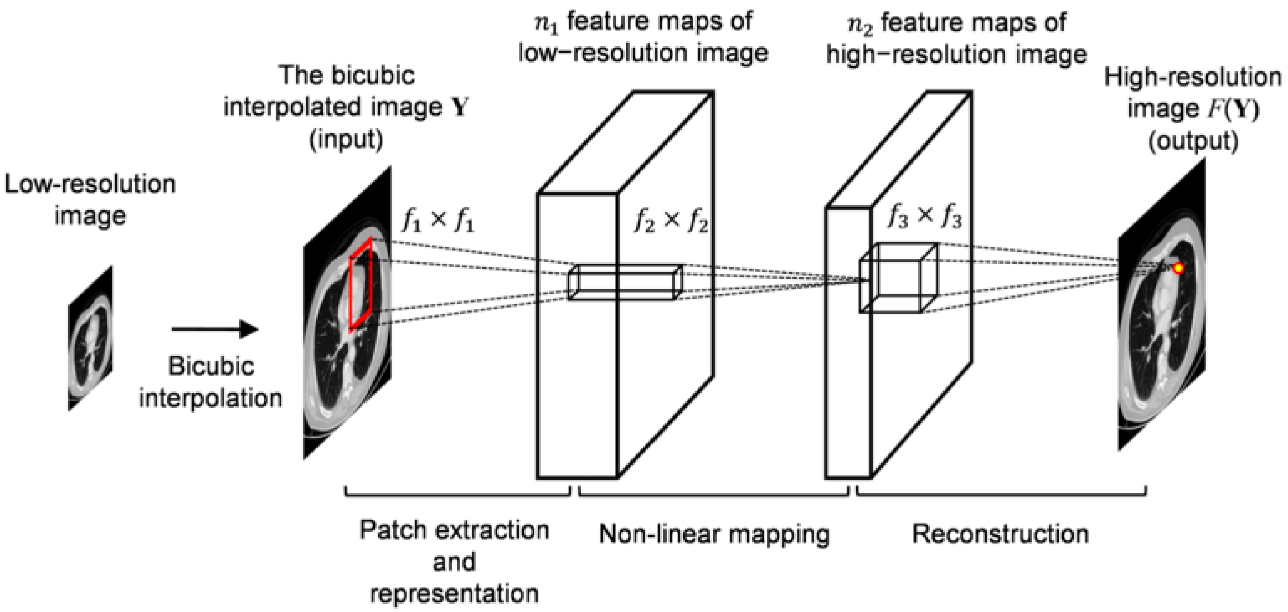
Proposed Approach 🛠️

- 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)



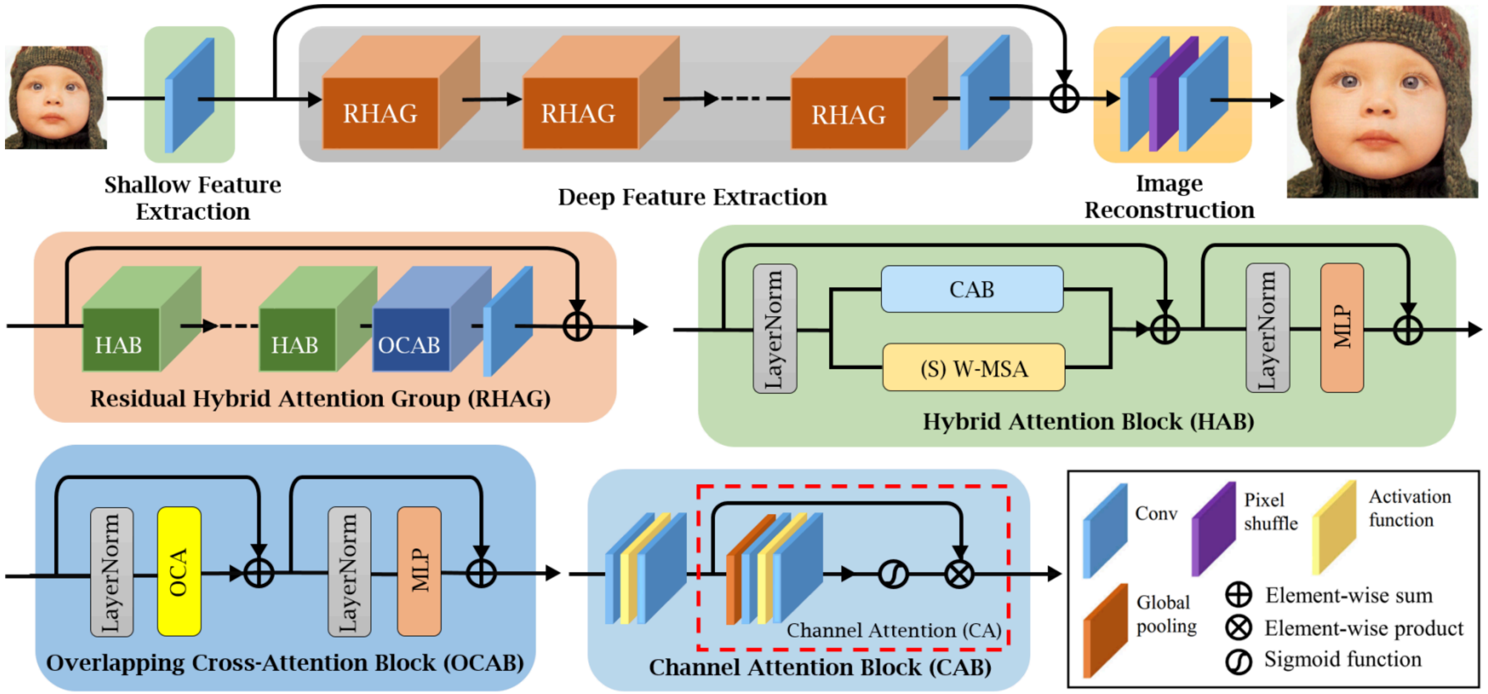
SRCNN 🧠

> 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 🚨

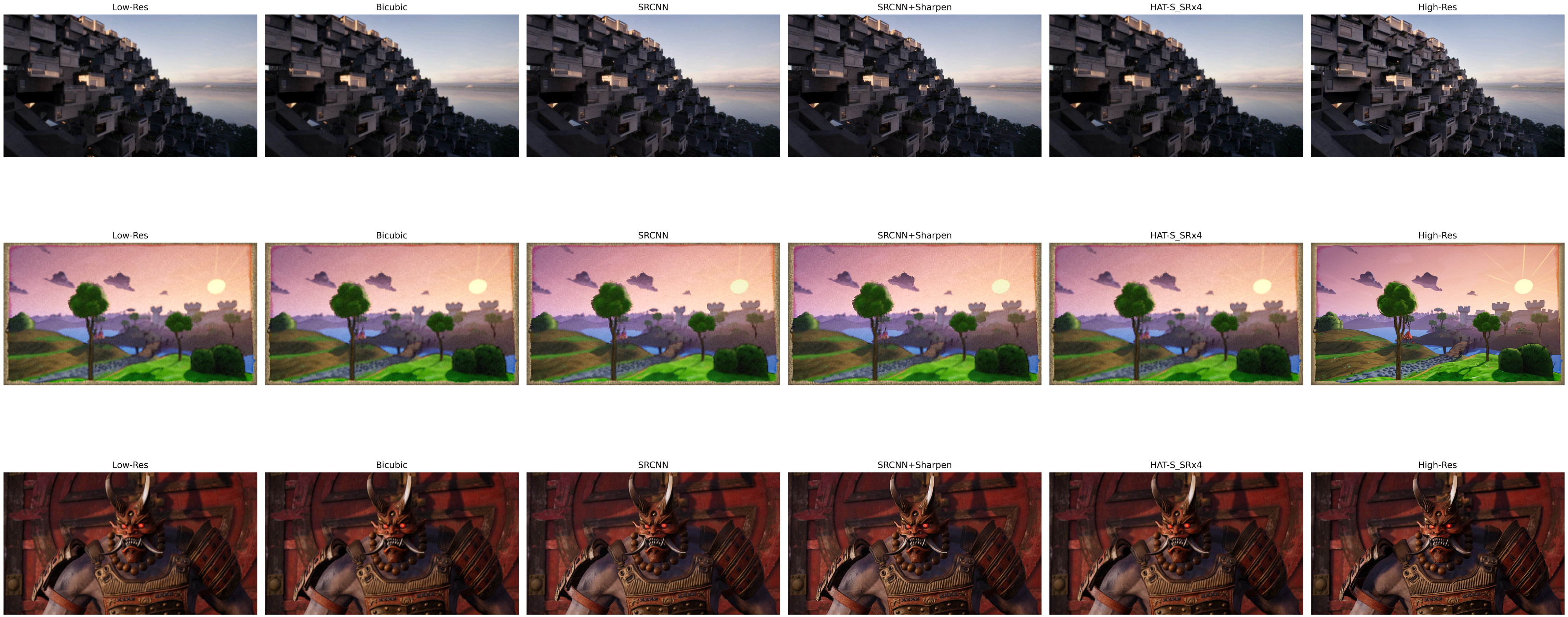
For evaluating the performance of the models, we used the following metrics:

- **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.

Experiments and Results 🚨

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

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+).
- Inference times could be measured, but we couldn't do that in this work.

Questions?