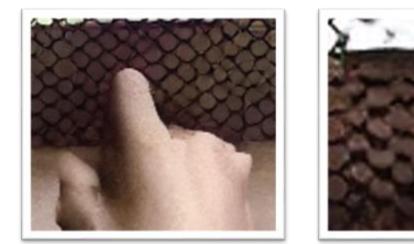
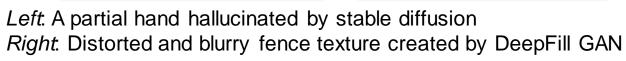
# Composite Inpainting

## Addressing Shortcomings in GAN and Patch-Based Inpainting with a Hybrid Approach Kai Zhu, Maria Alejandra Escalante University of Toronto

#### **Motivation**

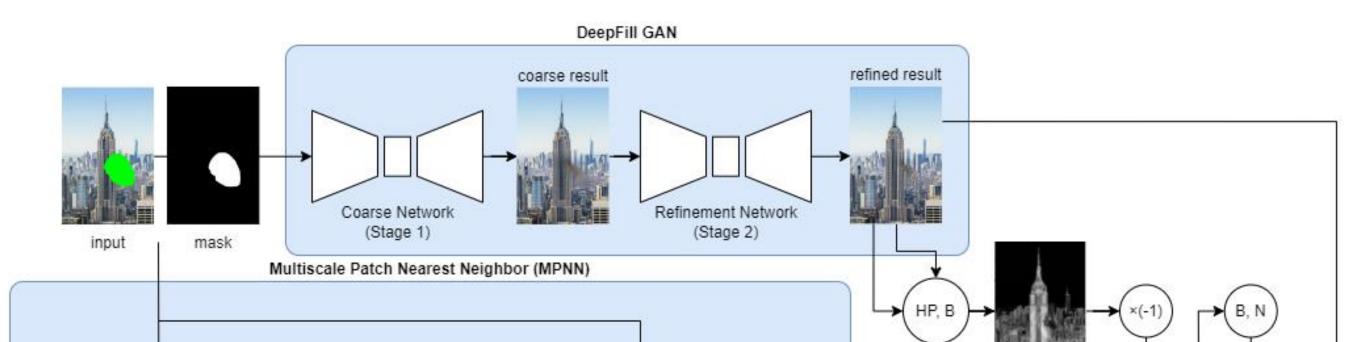
**Deep learning-based inpainting models** such as generative adversarial networks (GANs) and stable diffusion offer state of the art generation of realistic content in complex scenes using contextual surroundings. There exist, however, drawbacks for each method: GANs are difficult to train and often fail to capture textures effectively [1]; Stable diffusion is prone to hallucinations [2].





### **Methods**

- We implemented a multi-scale patch nearest neighbor (MPNN) method based on the architecture of GPNN[3] using the patchmatch algorithm.
  - $\circ$  Low scale  $\rightarrow$  generate structure
  - $\circ$  High scale  $\rightarrow$  generate texture
- Outputs of GAN and MPNN were composited using high-pass filter weighed blending to maximize texture density.
- Gabor filtering and refined patch nearest neighbor (RPNN, using coarse GAN output as PNN input) were also explored as alternative compositing methods.

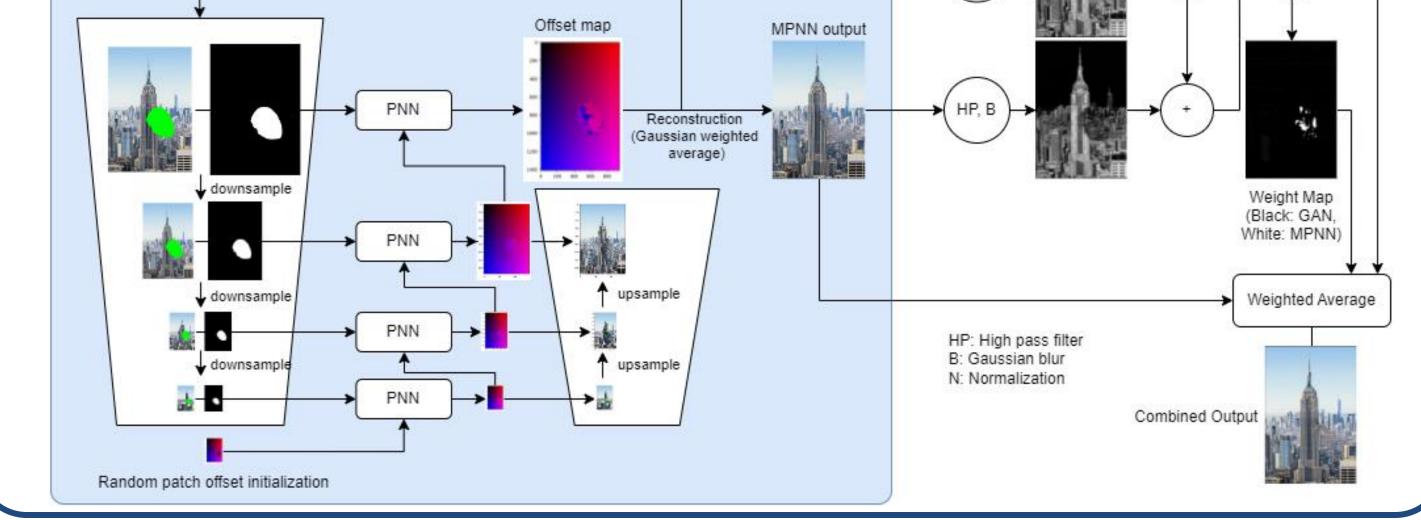


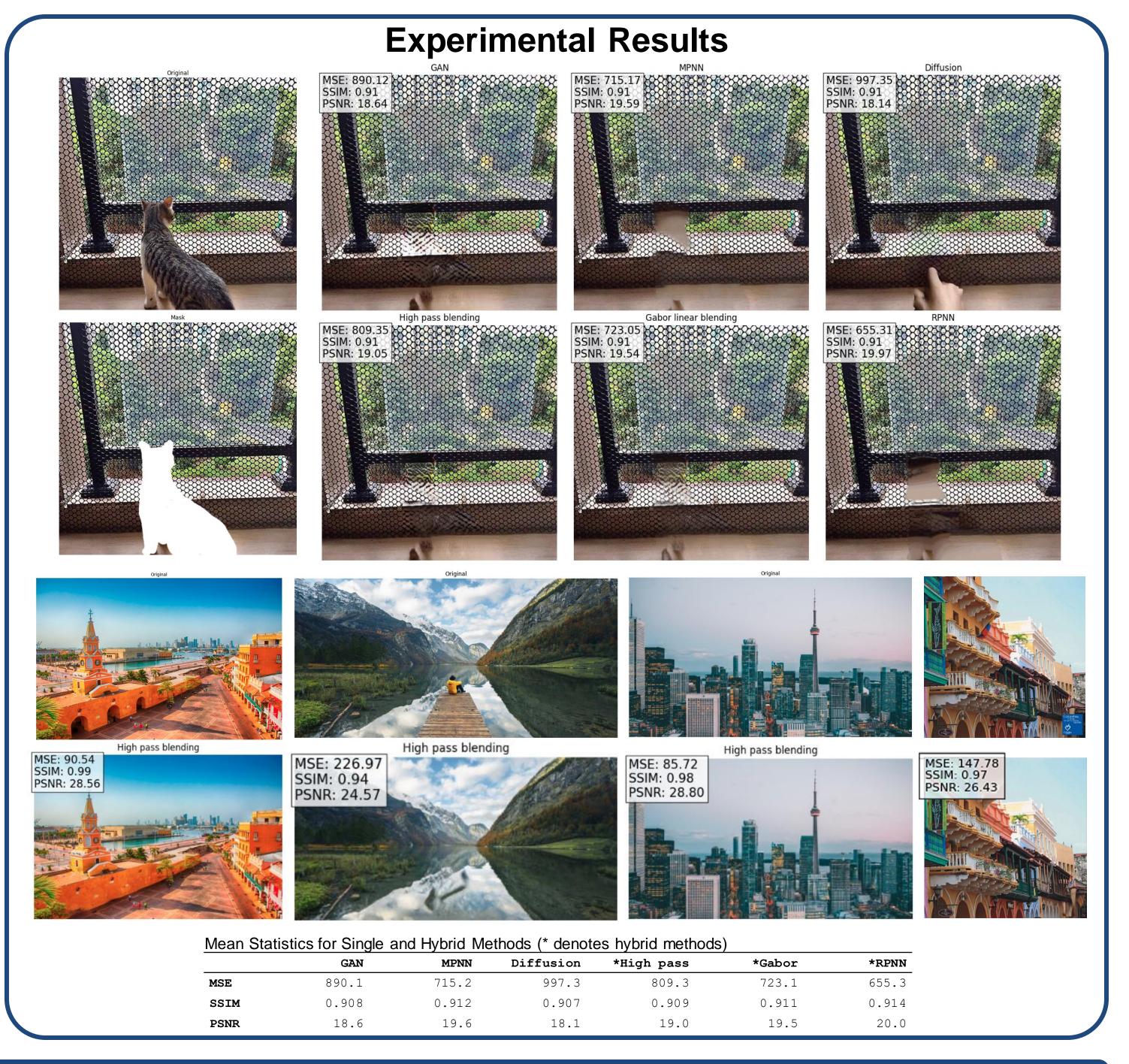
Classical **patch-based methods** reportedly excel at replicating textural details such as architectural features and repeating patterns, but encounter difficulty when generating larger structurally consistent content [1][3]. These methods also have the advantage of operating on a single image without requiring lengthy training time and data sets.

We propose a **hybrid approach** using GAN and patch-based methods in hopes of leveraging their strengths and minimizing their shortcomings to improve both structural and textural consistency.

#### **Related Work**

- Free-Form Image Inpainting with Gated Convolution presents a novel system using gated convolutions and SN-PatchGAN, enhancing inpainting quality and color consistency over prior methods [4].
- Generative Patch Nearest-Neighbor (GPNN) is an efficient, high quality patchbased single-image generation method.
  GPNN adopts SinGAN's multi-scale architecture while replacing the generator and discriminator with patch nearestneighbor modules [3].





- Latent diffusion models (LDM) introduced by Rombach et al. enhances efficiency and quality in high-resolution image synthesis and inpainting [5]. The runwayml/stablediffusion-inpainting model used in our comparison is based on this model.
- Gabor filters are recognized as a prominent method in texture classification applicable in textural analysis for inpainting. Bianconi et al [6] examine the impact of various Gabor filter parameters on texture discrimination. indicates research that while Their increasing frequencies and orientations has smoothing limited effect, parameters significantly classification enhance performance.

#### References

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