

# Diffusion Models in Dermatological Education: Flexible High Quality Image Generation for VR-based Clinical Simulations



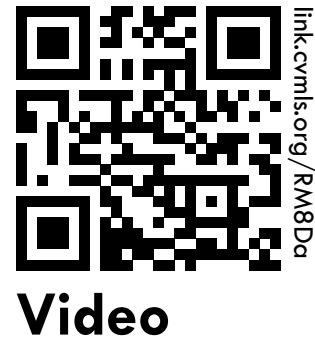
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Training medical students to accurately recognize malignant melanoma is a crucial competence and part of almost all medical curricula. We here present a pipeline to generate realistic high-resolution imagery of nevus and melanoma skin lesions by using diffusion models. To ensure the required quality and flexibility we introduce three novel guidance strategies and an adapted upsampling approach which enable the generation of user-specified shapes and to integrate the lesions onto pre-defined skin textures. We use our results in a virtual reality (VR) simulation for clinical education. The main advantages of synthetic over real images are the ability to facilitate adjustable learning scenarios and the preservation of patient privacy.



## Guided Sampling

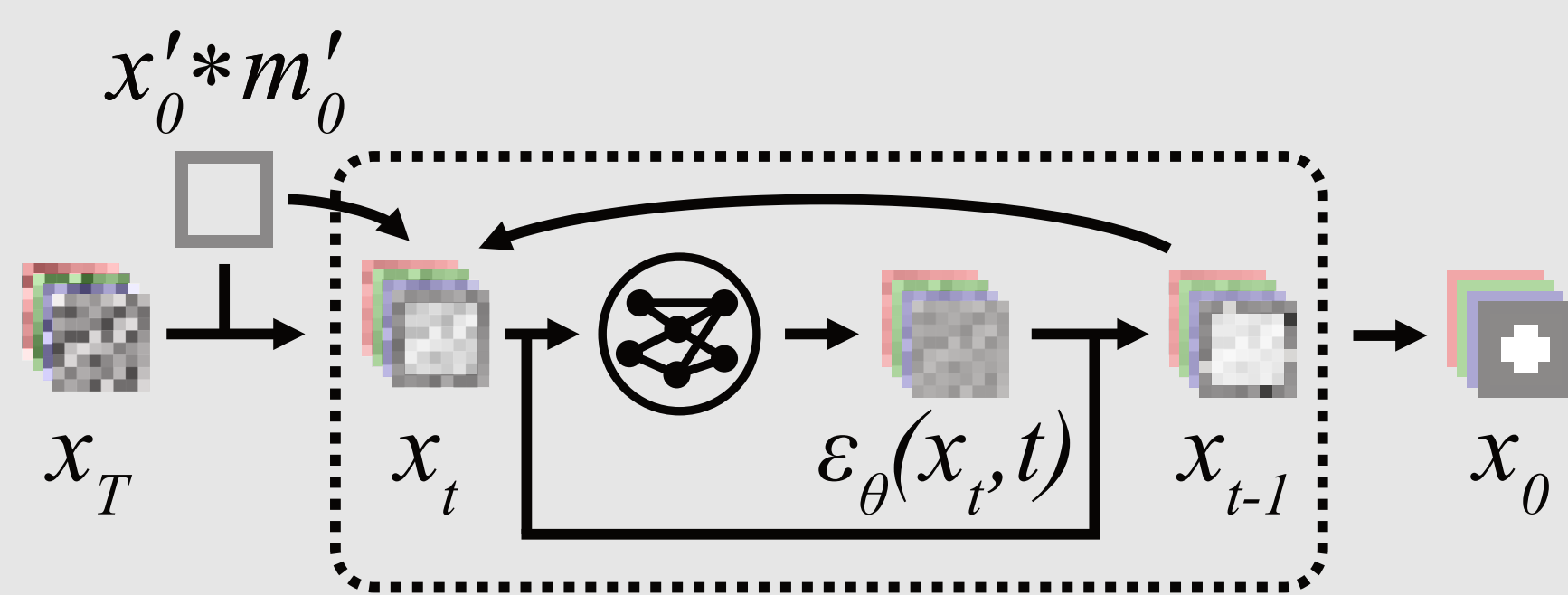


Figure 2: Enforced Class Border Guiding

During sampling we introduce three guiding mechanisms all based on the assumption that a certain region  $x'_0$  in the final image  $x_0$  is already known. Given a mask  $m'_0$  for this region the unguided sampling process can be extended as shown in Figure 2. Thanks to them, it is also possible to place lesions on the virtual agent (Figure 3).

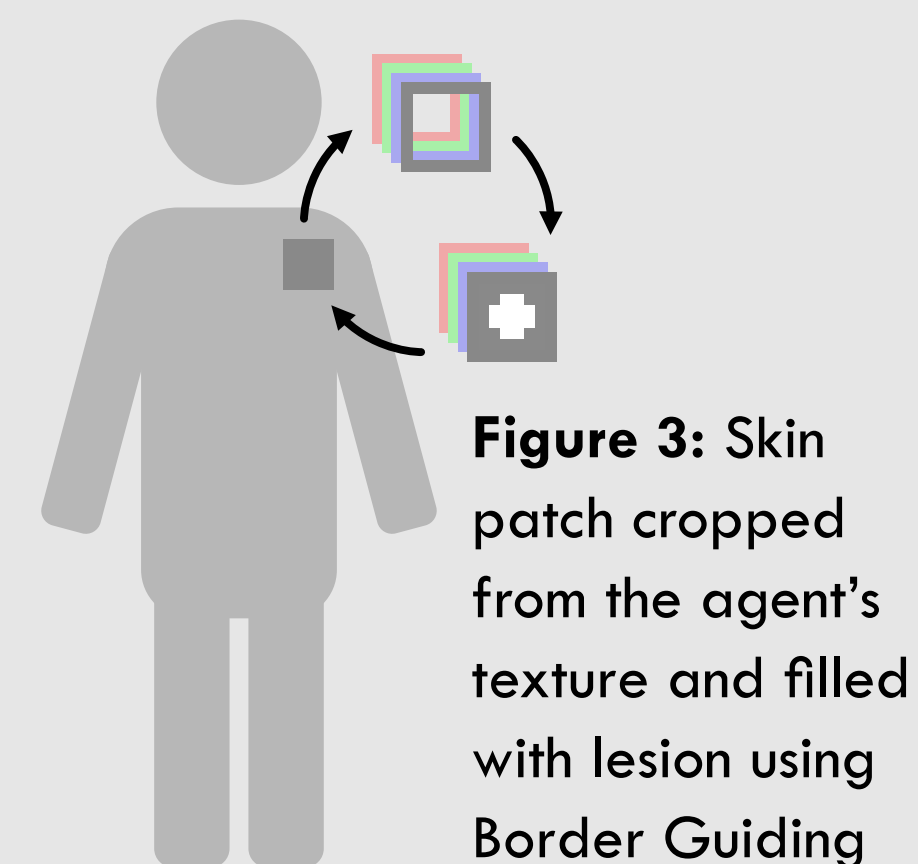


Figure 3: Skin patch cropped from the agent's texture and filled with lesion using Border Guiding

### Border Guiding

- Place on existing skin texture
- Pre-defined border region constant
- Only pixels within this border are generatively filled during the sampling process

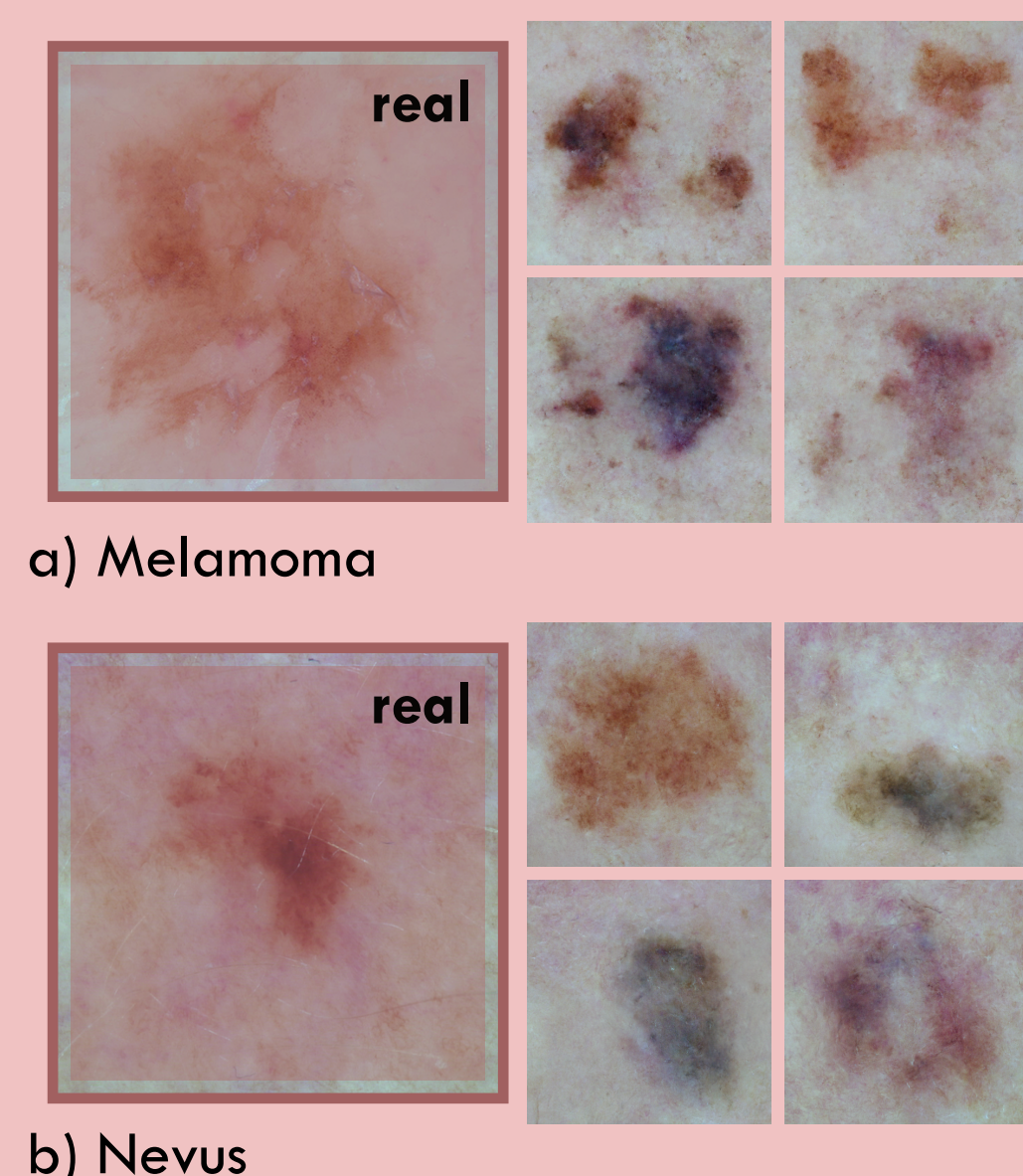


Figure 4: Border Guiding Results

### Segmentation Guiding

- Generate user-specified lesion shapes
- Segmentation mask channel constant
- Only color channels are generatively filled during the sampling process

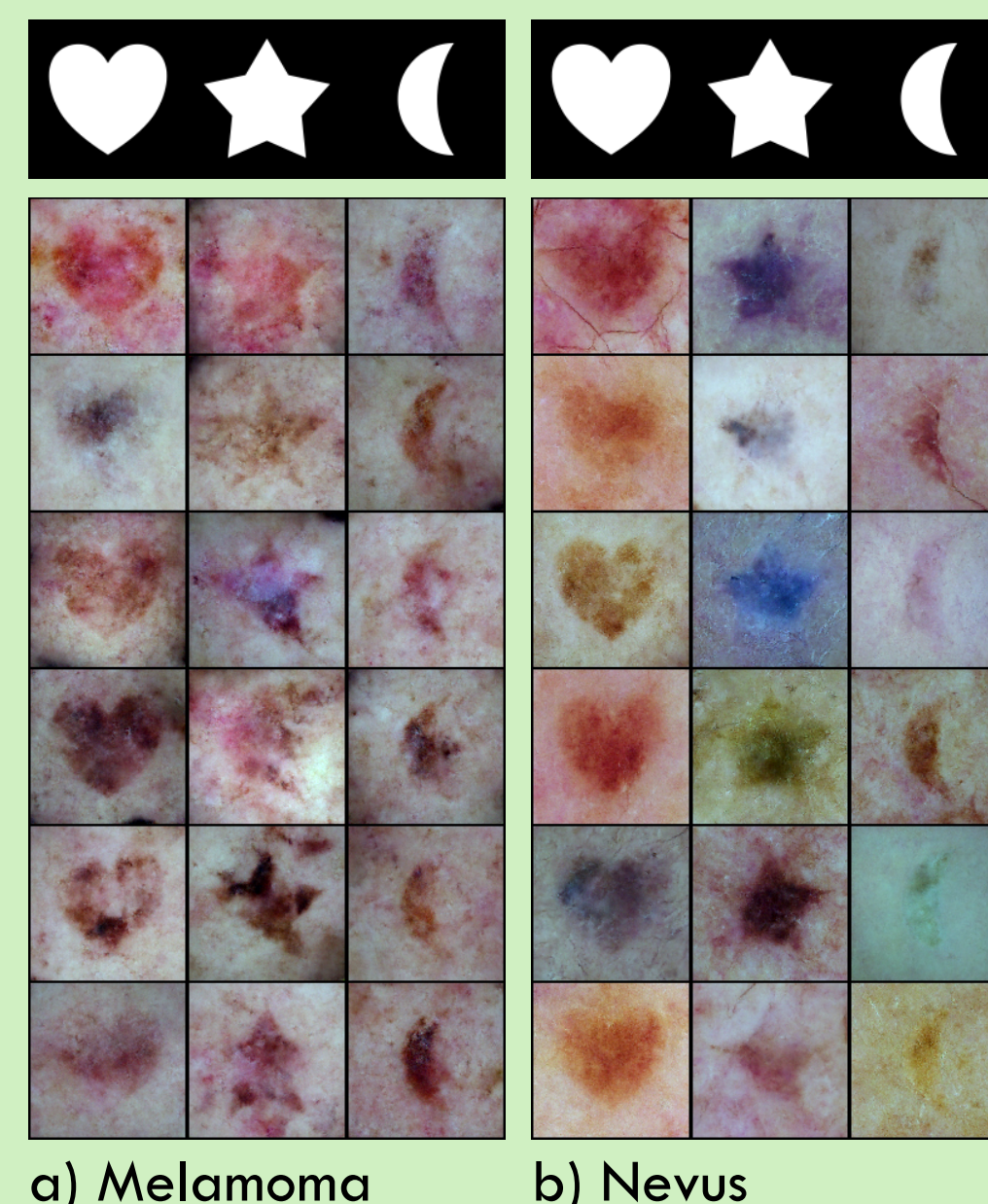


Figure 5: Segmentation Guiding Results

### Enforced Class Border Guiding

- Generation of images with non-cropped lesions
- Only the values in the segmentation mask of the border pixels are kept constant

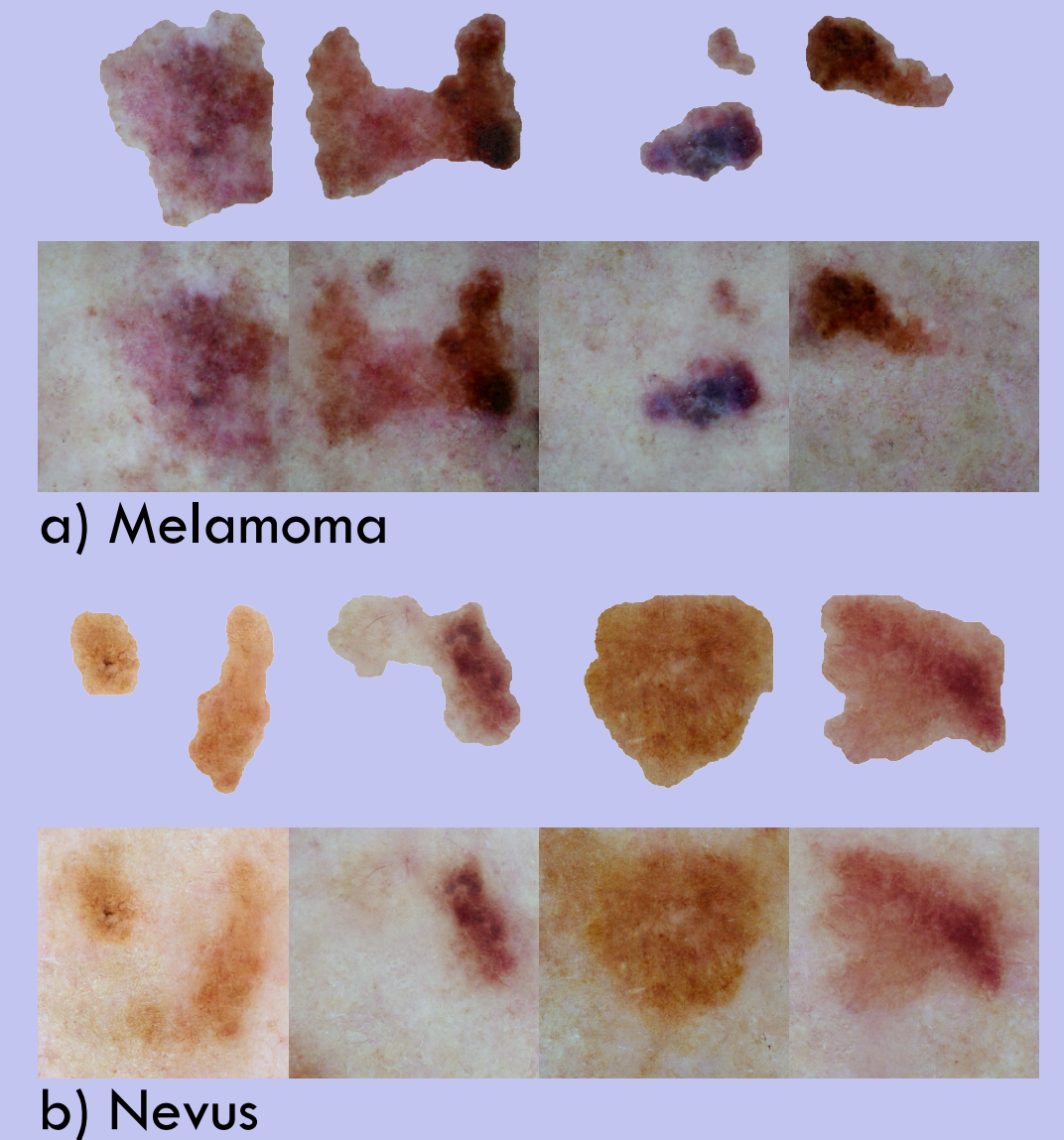


Figure 6: Class Enforced Border Guiding Results

## Tile Upsampling

We introduce Tile Upsampling, a strategy that recursively increases the resolution up to 454x454 by splitting the image into tiles, bilinear upsampling, adding noise, and denoising through DDPM iterations with the same trained model used for the initial generation (Figure 7). Our Border Guiding strategy is used to prevent seams in overlapping regions, and a novel Pool Guiding (Figure 8) addresses color consistency by comparing a downsampled noisy intermediate image with the low-resolution input version for guided sampling.

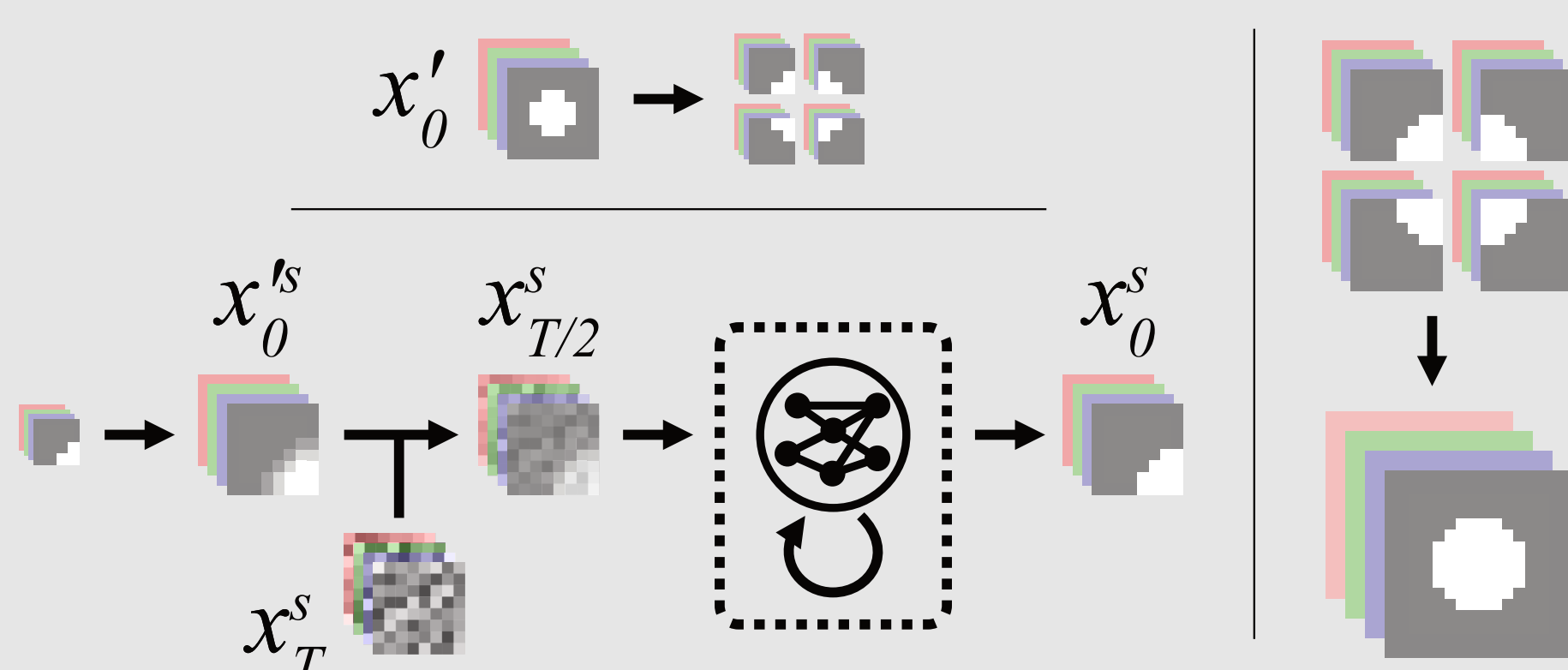


Figure 7: Tile Upsampling

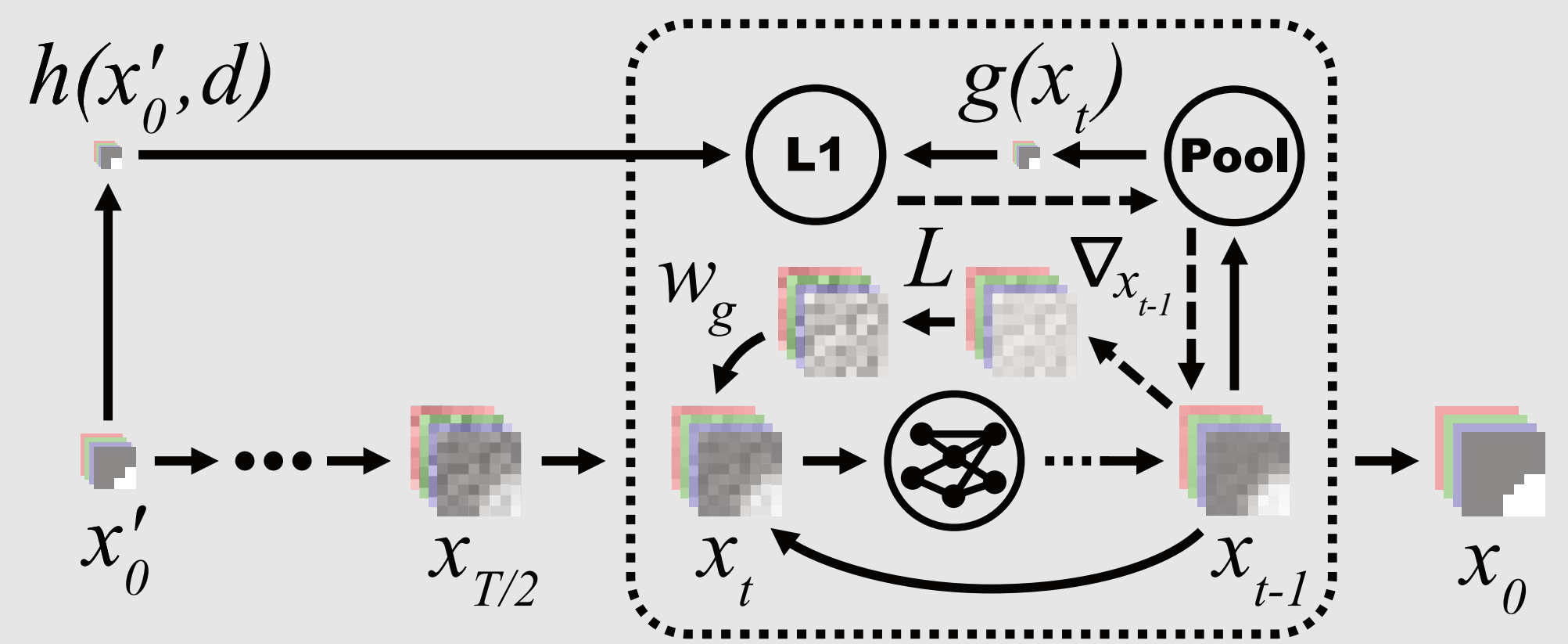


Figure 8: Pool Guiding during upsampling of one tile

## Training

Our architecture is based on the Denoising Diffusion Probabilistic Model (DDPM) with multiple adjustments, utilizing a U-Net-like neural network model  $\epsilon_\theta$  for the reverse diffusion process with a fixed size of 128x128 pixels and four channels (RGB + segmentation mask). We used separate models for melanoma and nevus classes due to better performance. The pipeline (Figure 1) involves training on the HAM10000 dataset from which we sampled random patches between 128x128 and 450x450 pixels. To preserve color information crucial for diagnosis, color normalization utilizing the segmentation masks is applied.

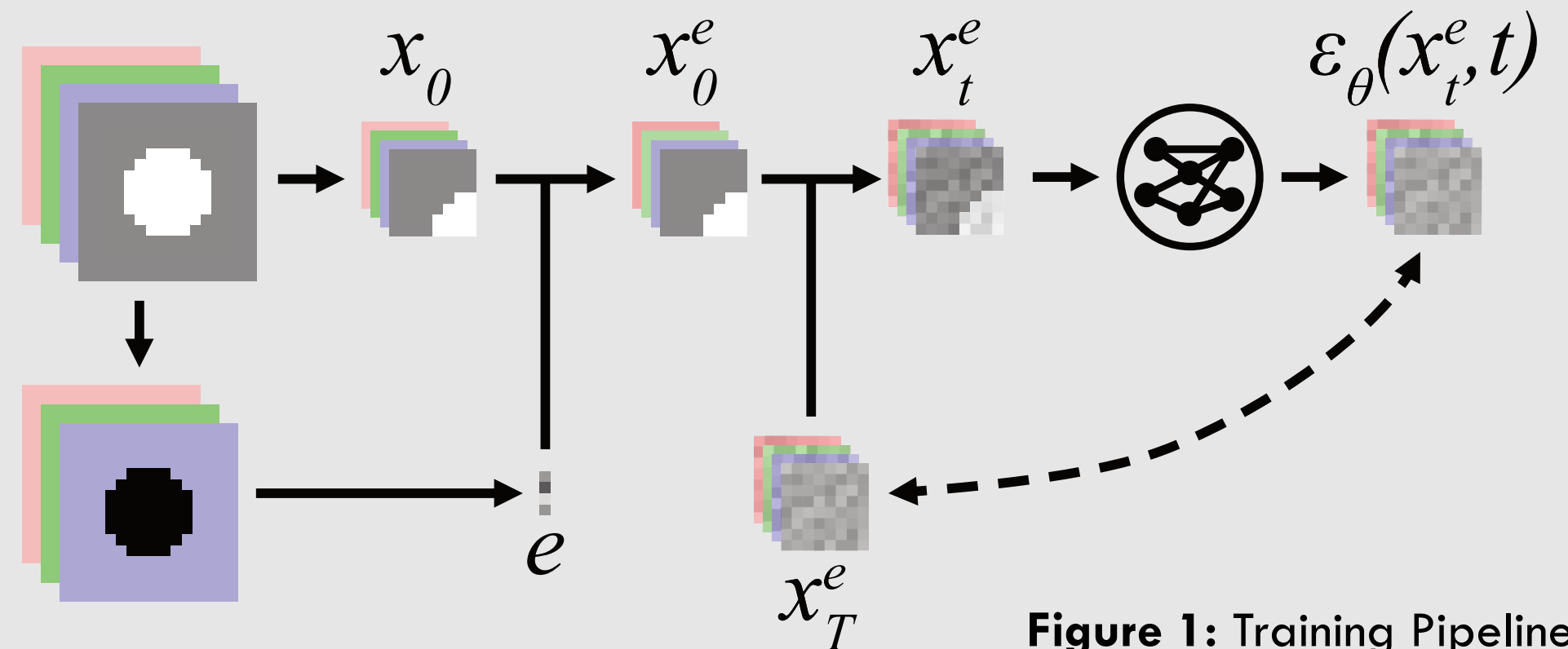


Figure 1: Training Pipeline