1. **Which approach performed better for this particular task of denoising?**

Average PSNR on test dataset for denoising with residual skip connections:
- Lambda 25: 12.8993 dB
- Lambda 50: 11.5892 dB
- Lambda 75: 10.7802 dB

Average PSNR on test dataset for denoising with the inception module:
- Lambda 25: 12.6581 dB
- Lambda 50: 11.2026 dB
- Lambda 75: 9.8998 dB

Given the information above, though only by a slight difference, denoising with **residual skip connections outperformed the inception module.** In the provided code, residual skip connections are implemented within the 'Autoencoder' class. These connections allow gradients to flow directly through the network, mitigating the vanishing gradient problem and making it easier to train deeper networks. In biomedical image denoising tasks, where preserving fine details is crucial, residual connections can help in retaining such information.

2. **What is the intuition behind the improved model which made it ideal for this particular task?**

Generally, the intuition behind the improved performance of the residual skip connections lies in their ability to preserve important image details and facilitate easier optimization, which is crucial for maintaining image fidelity in biomedical applications. A strategy used to address or mitigate optimization difficulties such as the vanishing gradient problem is skip connections. Compared to neural networks and simple convolution networks, skip connections have performance gains because it can support deeper networks with better accuracy.

Specifically, the code implemented the residual skip connections this way:

- The input image x first passes through the encoder, extracting high-level features.
- The output of the encoder then goes through the decoder to reconstruct the denoised image.
- Before adding the encoder output to the decoder output, a residual connection is introduced. This connection consists of a small convolutional block (self.residual) that processes the input image directly.
- The output of the residual block (x_res) is added to the decoder output (x) using element-wise addition.

In this implementation, the residual connections are added between the encoder and decoder sections of the autoencoder. The intuition behind skip connections has to do with providing a shortcut that allows the network to identify the difference between input and target output which reflects its capability to directly learn residual mappings. The shortcut allows the model to concentrate on a more manageable scale, given that residuals are smaller and thus easier to model than the entire output. This is particularly beneficial for denoising tasks, where the goal is to recover the clean image from the noisy input.

Meanwhile, the inception module extracts features at multiple scales by use of parallel convolutional branches of different kernel sizes. This can help in capturing both local and global information within the image, which is beneficial for tasks like denoising. However, the architecture of the inception module is more complex than traditional layers. This complexity then leads to difficulties in designing and training the module. Thus, in this scenario, the residual skip connections were able to perform better.

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