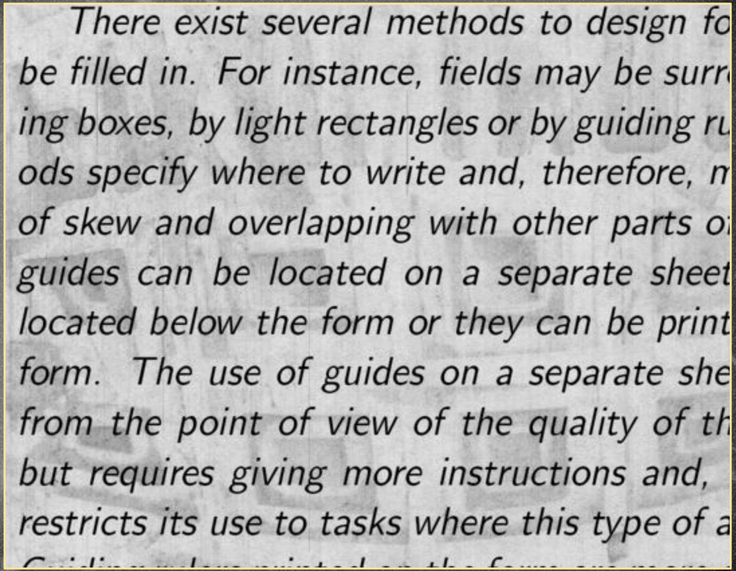
IMAGE DENOISING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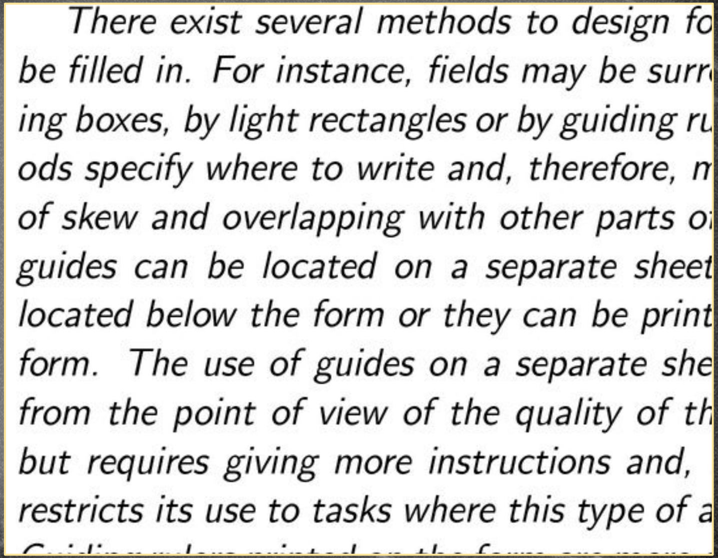
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ENCODER

python

```python
# Encoder
x = Conv2D(32, (3,3), activation='relu', padding='same', name='Conv1')(input_img)
x = MaxPooling2D((2,2), padding='same', name='pool1')(x)
x = Conv2D(64, (3,3), activation='relu', padding='same', name='Conv2')(x)
x = MaxPooling2D((2,2), padding='same', name='pool2')(x)
```

DECODER

python

```python
# Decoder
x = Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3')(x)
x = UpSampling2D((2,2), name='upsample1')(x)
x = Conv2D(32, (3,3), activation='relu', padding='same', name='Conv4')(x)
x = UpSampling2D((2,2), name='upsample2')(x)
x = Conv2D(1, (3,3), activation='sigmoid', padding='same', name='Conv5')(x)
```

The **encoder** part of the network compresses the input image into a lower-dimensional representation (latent space). This is crucial for denoising because:

- It extracts **important features** from the noisy image while discarding irrelevant noise.
- The pooling layers in the encoder reduce the spatial dimensions, which helps in focusing on the **global structure** of the image rather than local noise.

Example:

- Input: Noisy image (420x540x1)
- Encoder Output: Compressed representation (105x135x64)

The **decoder** part reconstructs the clean image from the compressed representation. It does this by:

- Upsampling the compressed features back to the original image size.
- Using learned patterns to **reconstruct the clean image** while suppressing noise.

Example:

- Decoder Input: Compressed representation (105x135x64)
- Decoder Output: Denoised image (420x540x1)

Noise Removal Mechanism

The encoder-decoder architecture inherently learns to separate noise from the image because:

- Noise is typically **high-frequency and random**, while the actual image content is **structured and low-frequency**.
- The encoder's pooling layers **suppress high-frequency noise** by downsampling.
- The decoder reconstructs the image using the **low-frequency, noise-free features** extracted by the encoder.

End-to-End Learning

The encoder-decoder architecture allows the model to learn the entire denoising process in an **end-to-end manner**:

- The model is trained on pairs of noisy and clean images.
- It learns to map noisy inputs to clean outputs directly, without requiring handcrafted features or preprocessing steps.

Why Not Use a Simple CNN?

A simple CNN without an encoder-decoder structure:

- May not effectively compress and reconstruct the image.
- Could overfit to noise instead of learning to remove it.
- Lacks the **bottleneck layer**, which is critical for forcing the network to focus on important features.

Thank You for Your Attention!

We hope this presentation provided valuable insights into the power of **Encoder-Decoder Architectures** for Image Denoising.