Image Super-Resolution Using Deep Learning

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Problem Statement

Problem : Given a low-resolution image, we need to develop a deep learning model to create a high-resolution version by inferring missing image details.

Challenges

- **Ill-posed problem:** There can be multiple high-resolution images that could have resulted in the same low-resolution image. The model needs to learn the best possible reconstruction.
- **Preserving detail:** The model needs to not only increase resolution but also recover lost details and textures from the low-resolution image.
- **Avoiding artifacts:** The reconstruction process should not introduce unwanted artifacts like noise or unnatural sharpening.

Literature Review & Motivation (0)

Convention models for SR tasks :

- **Convolutional Neural Networks(CNN) based models:**
  - Computationally efficient.
  - Can learn well from smaller datasets due to their inductive bias (ability to generalize from limited data).
  - However, CNNs struggle to capture long-range dependencies between different parts of the image.
- **Vision Transformer (VT) based models:**
  - Excel at capturing long-range dependencies due to their self-attention mechanism.
  - However, require a large amount of training data and computational resources, limiting their use in scenarios with limited data and GPUs.
  - VTs lack the inductive bias of CNNs.

Literature Review & Motivation (1)

- **Wavelet based models:**
    - Leverage the power of wavelet transforms to decompose images into approximation (coarse) and detail (fine) information.
    - *Advantages:*
        - Wavelet decomposition simplifies mapping between low-resolution and high-resolution images.
        - Invertible wavelet transform ensures no information loss during downsampling
    - *SR with Wavelets:*
        - Models like DWSR use CNNs to predict detail coefficients in wavelet space for HR image reconstruction.
        - WaveletSRNet focuses on faces, predicting wavelet coefficients for reconstruction.
        - MWCNN replaces pooling with wavelets in CNNs, preserving information for better long-range dependency capture.

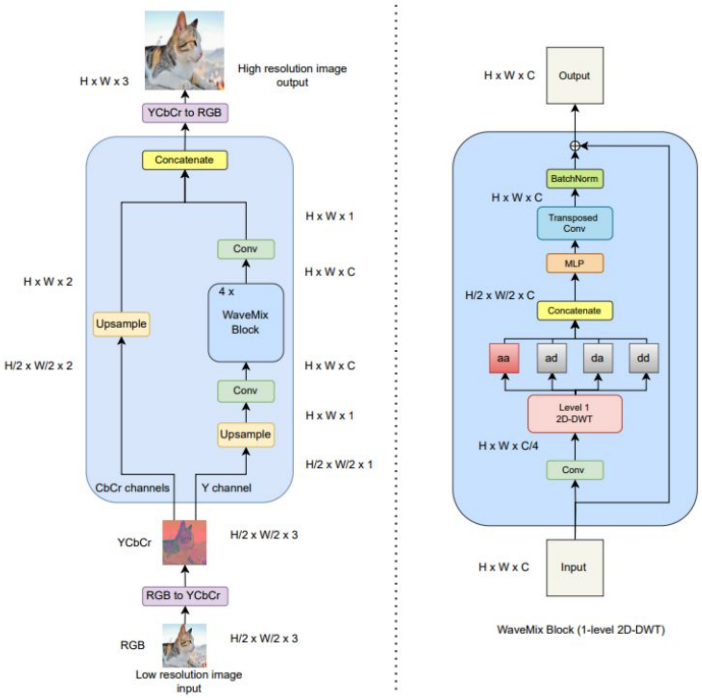
WaveMixSR (0)

- Wavelet based model, that combines the strength of both CNN and VT based models.
- Utilizes spatial token-mixing using a 2D discrete wavelet transform (DWT) for efficient communication between different image regions.
- Usage of 2D DWT, makes it computationally efficient and requiring less training data compared to pure VT models.

- **Architecture (Dual-Path Processing):**
  - Y-channel (luminance): Prioritized for detail reconstruction due to higher information content.
  - CbCr channels (chrominance): Upsampled directly.

WaveMixSR (1)

- **WaveMix Blocks (Y-channel path):**
  - Core component for detail reconstruction and sharpening.
  - Convolution for learnable feature extraction.
  - 2D-discrete wavelet transform (DWT)
  - MLP for channel-wise feature mixing.
  - Transposed convolution to restore spatial resolution.
  - Residual connection for improved gradient flow.
- **Upsampling:**
  - Efficient non-parametric methods (bilinear or bicubic interpolation).



Research Gaps

- **Exploration of Variations in Wavelet Transform:** The study uses 2D-discrete wavelet transform (DWT) for spatial token-mixing. Investigating the effects of using different wavelet families or modifying the DWT implementation could potentially improve performance or efficiency.

- **Incorporating External Knowledge:** The paper focuses on the WaveMixSR architecture itself. How WaveMixSR might benefit from incorporating external knowledge sources, such as image priors or pre-trained, is an unexplored area.

- **Incorporating Adversarial Training:** Adversarial Training has been shown to improve the visual quality of super resolved images compared to normal training. WaveMixSR with adversarial training is an unexplored research zone.

Our Contribution & Experiments (0)

- **Wavelet Family Selection**
  - **Objective:** To determine the best wavelet family for WaveMixSR.
  - **Exploration:** Examined three wavelet families—Haar, DB1, and Symlet.
  - **Evaluation Criteria:** Measured performance using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), focusing on noise levels and image border artifacts.
  - **Outcome:** Haar wavelet provided the best results, with high PSNR and SSIM, and minimal noise. This led to its selection for the WaveMixSR.

Our Contribution & Experiments (1)

- **Pre-Trained Network Selection**
  - **Objective:** To enhance feature extraction capabilities for WaveMixSR.
  - **Pre-Trained Networks:** Considered VGG11 and ResNet18, selecting specific layers for feature extraction.
  - **ResNet18 Selection:** Outperformed VGG11, offering more accurate image representation and residual learning benefits.
  - **Selected Layers:**
    - conv1, bn1, relu, and maxpool: Early feature extraction and spatial downsampling.
    - layer1 and layer2: Residual blocks for complex feature learning.
  - **Outcome:** Integration of ResNet18 provided a strong foundation for feature extraction, leading to more accurate super-resolution results.

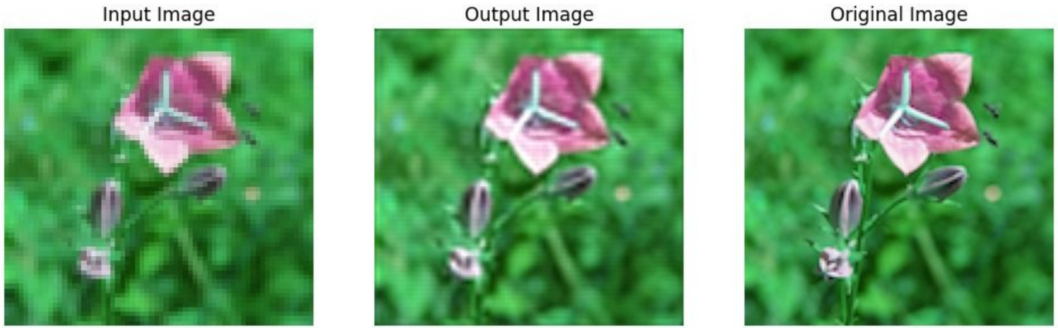
Our Contribution & Experiments (2)

- **Adversarial Training Integration**
  - **Objective:** To create more realistic high-resolution images through adversarial training.
  - **GAN Framework:** Introduced a generator (WaveMixSR with ResNet18 backbone) and a discriminator for adversarial training.
  - **Discriminator Design:**
    - Combination of convolutional layers, batch normalization, and fully connected layers.
    - Dropout applied to prevent overfitting.
    - Role: Distinguish real images from generated images, challenging the generator to improve.
  - **Generator Enhancement:** The WaveMixSR generator, backed by ResNet18, was improved through adversarial training to produce more realistic outputs.
  - **Outcome:** Adversarial training led to significant improvements in image quality, with the generator producing more realistic high-resolution images. The setup enhanced both perceptual quality and computational efficiency, demonstrating the effectiveness of integrating GAN-based approaches into super-resolution tasks.

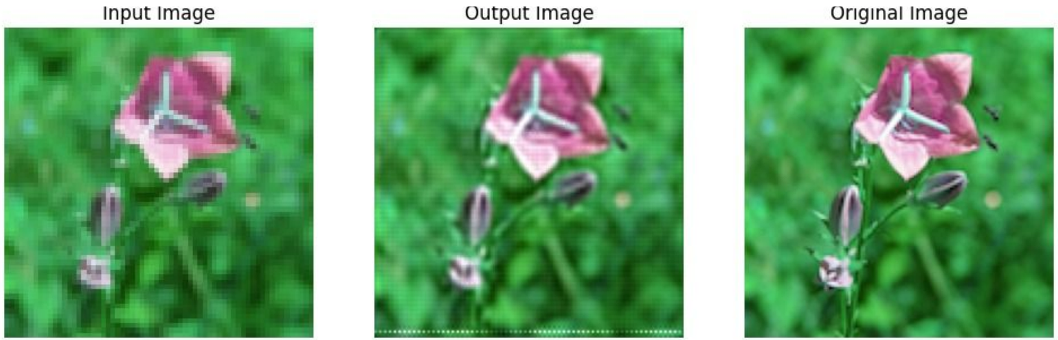
Results and Discussion (0)

- **Results**
  - **PSNR:**
    - Haar Wavelet: 29.1
    - DB1 Wavelet: 28.45
    - Symlet Wavelet: 28.7
  - **SSIM:**
    - Haar Wavelet: 0.87
    - DB1 Wavelet: 0.79
    - Symlet Wavelet: 0.81

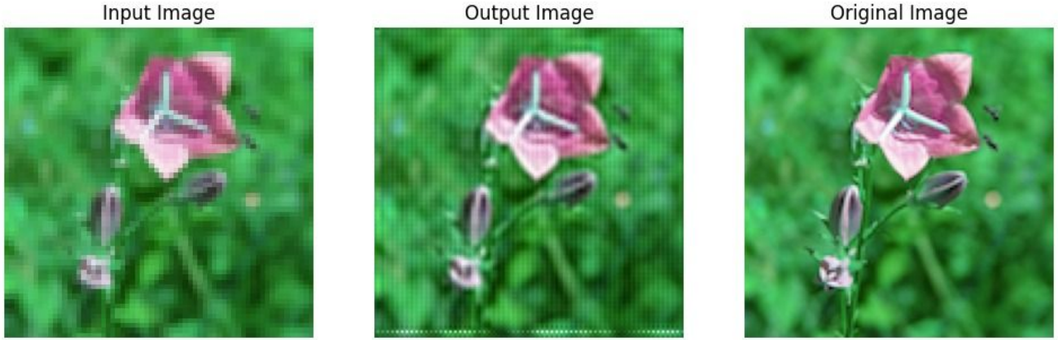
- **Key Takeaways**
  - Haar wavelet showed the highest PSNR and SSIM, indicating better image quality.
  - DB1 and Symlet wavelets exhibited increased noise at the image borders.
  - Based on these results, Haar wavelet was chosen for WaveMixSR, offering improved image reconstruction with minimal artifacts.



Haar Wavelets



DB1 Wavelets



Symlet Wavelets

Results and Discussion (1)

- **Results (PSNR)**
  - VGG11: 31.1 (at 20 epochs)
  - ResNet18: 32.5 (at 20 epochs)

- **Visual Analysis:**
  - ResNet18 produced results that were closer in appearance to the original high-resolution images.
  - VGG11 yielded grainier results compared to ResNet18.

- **Key Takeaways**
  - ResNet18 outperformed VGG11 in both PSNR and visual similarity to the original images.
  - The improved results with ResNet18 suggest its stronger feature extraction capabilities and residual learning benefits.
  - This led to the decision to integrate ResNet18 into the WaveMixSR model, ensuring higher-quality super-resolution.

ResNet18

VGG11

Results and Discussion (2)

- Results
    - **PSNR:**
        - After 20 epochs of adversarial training, PSNR reached 34.46, indicating a significant improvement in image quality.
    - **Discriminator Loss:**
        - True Cross-Entropy Loss: 0.0011899899538150589
        - False Cross-Entropy Loss: 0.00041642620717529 67
- Key Takeaways
    - Adversarial training with the GAN framework significantly improved image quality.
    - The high PSNR and low discriminator loss suggest that the generator achieved better realism and detail reconstruction.

Input Image

Output Image

Original Image

Thank You

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